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The Cognitive Reserve Hypothesis: A Longitudinal Examination of Age-Associated Declines in Reasoning and Processing Speed

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The term *cognitive reserve* is frequently used to refer to the ubiquitous finding that, during later life, those higher in experiential resources (e.g., education, knowledge) exhibit higher levels of cognitive function. This observation may be the result of either experiential resources playing protective roles with respect to the cognitive declines associated with aging or the persistence of differences in functioning that have existed since earlier adulthood. These possibilities were examined by applying accelerated longitudinal structural equation (growth curve) models to 5-year reasoning and speed data from the no-contact control group ($N = 690$; age 65–89 years at baseline) of the Advanced Cognitive Training for Independent and Vital Elderly study. Vocabulary knowledge and years of education, as markers of cognitive reserve, were related to levels of cognitive functioning but unrelated to rates of cognitive change, both before and after the (negative) relations between levels and rates were controlled for. These results suggest that cognitive reserve reflects the persistence of earlier differences in cognitive functioning rather than differential rates of age-associated cognitive declines.

Keywords: cognitive reserve, brain reserve, education, cognitive decline, aging

One particularly important and long-standing topic within the social, behavioral, and cognitive sciences concerns the role that the environment plays with respect to our interactions, behaviors, and cognitive functioning (Sternberg & Grigorenko, 1997). Levels of educational attainment and products of educational achievement such as knowledge and literacy are particularly meaningful indices of environmental quality that have well-established relations with cognitive performance throughout the lifespan (Salthouse, 1991).

Much research has focused on childhood development and on determination of the causal direction of the education–cognition relation. There is a good deal of evidence to suggest that this relation is reciprocal during childhood (Ceci, 1996; Crano, Kenny, & Campbell, 1972; Dickens & Flynn, 2001; cf. Jensen, 1998). Researchers have also begun to investigate the possibility that having had an enriched environment during earlier parts of one's life may play a protective role with respect to the cognitive deficits associated with adult aging (Satz, 1993; Stern, 2002). Hypotheses addressing the late-life education–cognition relation have been generally referred to as *cognitive reserve* hypotheses.[1] The major issue that has not yet been resolved with respect to this group of hypotheses, and is the focus of this article, is whether the late-life relations between education and cognitive performance reflect (a) a relation between the quality of earlier life environment and rates of age-associated cognitive declines or (b) the persistence of education–cognition relations that have existed since earlier adulthood.

Evidence From Prevalence and Incidence Studies of Dementia

Perhaps the most interesting findings regarding cognitive reserve hypotheses were by Snowdon et al. (1996), who found that linguistic ability among nuns at a mean age of 22 years was

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[1] The cognitive reserve hypothesis is sometimes distinguished from the similar brain reserve hypothesis. The brain reserve hypothesis is discussed in detail by Christensen, Anstey, Leach, and Mackinnon (2008), who explain that "the hypothesis is that high premorbid intelligence, education, an active, stimulating lifestyle, or a physically larger brain provide reserve capacity which protects the individual from the negative effects of aging and disease on brain function" (p. 135).

predictive of their cognitive performance and the risk of Alzheimer's disease approximately 58 years later. A similar study by Whalley et al. (2000) found that compared with a matched control group of nondemented individuals, those suffering from dementia at age 72 years or older had scored significantly lower on mental ability tests at 11 years of age. These findings have been bolstered by studies (e.g., The Canadian Study of Health and Aging, 1994) reporting higher prevalence rates of dementia in lower education groups. In fact, a meta-analysis of longitudinal studies, conducted by Valenzuela and Sachdev (2006), found that reserve, as indexed by variables such as education, occupation, premorbid IQ, and mental activities, was associated with lower risks for incident dementia.

Evidence From Longitudinal Studies of Cognitive Change

A number of longitudinal studies have examined the relations between hypothesized protective factors and actual cognitive change in both normal and demented adults. Bosma, van Boxtel, Ponds, Houx, and Jolles (2003), for example, found that in a group of 708 individuals age 50–80 years, 3-year declines in serial list recall, Stroop color word, and Mini-Mental State Examination (MMSE) scores were more shallow for those who reported higher levels of educational attainment. Lyketsos, Chen, and Anthony (1999) reported similar findings with respect to a longitudinal study spanning approximately 12 years. In this study, greater declines (2.5 points compared with 1.4 points) in MMSE scores were associated with having 8 or fewer years of education. It is also notable that baseline scores were systematically associated with magnitude of decline (a baseline score of 30 was associated with a 1.23-point decrement, whereas a baseline score of 24 or less was associated with a 2.3-point decrement). Finally, Manly, Touradji, Tang, and Stern (2003) used literacy as an index of quality of education and demonstrated that the rate of decline in word list recall performance over approximately 5 years was steeper for low-literacy individuals than for high-literacy individuals. Literacy was also positively associated with higher cognitive performance at all assessment occasions.

In seeming contradiction to these findings, Andel, Vigen, Mack, Clark, and Gatz (2006) found that among patients with a confirmed Alzheimer's disease diagnosis, higher education was related to faster declines in MMSE scores over an average of 2.5 years. Education was positively related to baseline scores. Interestingly, these results were interpreted to mean that greater reserve is related not only to the postponement of dementia but also to accelerated cognitive decline after the onset of dementia symptoms. Similar results have been found by Stern, Albert, Tang, and Tsai (1999); Teri, McCurry, Edland, Kukull, and Larson (1995); and Unverzagt, Hui, Farlow, Hall, and Hendrie (1998).

Partially contradictory findings have also been reported by Christensen, Hofer, and their colleagues (Christensen et al. 2001; Hofer et al., 2002; Mackinnon, Christensen, Hofer, Korten, & Jorm, 2003), who found evidence for a relation between education and levels of memory, speed, and verbal performance but no evidence for a relation between education and 7-year changes in performance. Moreover, in a series of dynamic longitudinal investigations, Ghisletta and colleagues (Ghisletta & Lindenberger, 2003, 2004; Ghisletta & de Ribaupierre, 2005) have demonstrated that changes in culture-based (crystallized or pragmatic; e.g., vocabulary knowledge) abilities are predicted by levels of process (fluid or mechanic; e.g., processing speed) abilities better than changes in process abilities are predicted by levels of culture-based abilities. For a comprehensive review of relevant longitudinal studies published before 2000, see Anstey and Christensen (2000).

Theories of Cognitive Reserve

A useful standard when comparing theoretical models is to focus on their conflicting predictions. Among the most salient and testable predictions, in the case of cognitive reserve models, are those concerning rates of decline in cognitive performance. Models predicting moderation explain that high-reserve people are better able to maintain their levels of performance relative to low-reserve people, who decline more rapidly, resulting in increased performance differences over time. This prediction is similar to what has been termed *differential preservation* with respect to the mental exercise hypothesis (Salthouse, 2006; Salthouse, Babcock, Skovronek, Mitchell, & Palmon, 1990). Alternatively, there are models that predict stability of performance differences. These models explain that although high- and low-reserve people differ in their levels of cognitive performance, their rates of decline in performance are comparable. This prediction is similar to what has been termed *preserved differentiation* (Salthouse, 2006; Salthouse et al., 1990). Theories of active and passive cognitive reserve processes are now introduced and evaluated with respect to their implications for differential preservation versus preserved differentiation.

Stern (2002) has proposed that cognitive reserve mechanisms are active processes through which, in response to neurobiological degradation, the brain actively attempts to compensate by using either brain networks or cognitive paradigms that are less susceptible to disruption. Such active models would predict that, all else being equal, more highly educated people, or individuals possessing more knowledge, would be able to postpone reaching clinical levels of impaired cognitive functioning. Salthouse (2003) has proposed five possible mechanisms by which this might occur: (a) Knowledge can enhance memory in the form of richer and more elaborate encoding and more effective retrieval cues facilitated by a superior organizational structuring of information; (b) knowledge can result in easier access to relevant information and better organized representations of the problem, resulting in enhanced problem solving skills; (c) knowledge of past consequences of various alternatives can provide an effortless means of making accurate predictions regarding future consequences; (d) knowledge can enable reliance on previously compiled efficient algorithms, rather than on slow and controlled processes; and (e) knowledge of prior solutions to familiar problems can reduce online processing requirements. All of these possible mechanisms, however, should result in differential rates of decline (moderation) only if they are increasingly relied upon, or if they are of increasing advantage, with increasing neurobiological disintegrity. Rather, we argue, there is no strong reason to doubt that these mechanisms are equally relied upon, or equally advantageous, at all ages and levels of functioning. Therefore, active cognitive reserve models fit the stability, or preserved differentiation class, and do not necessarily lead to the hypothesis of steeper cognitive decline among those with less enriched environmental backgrounds.

Passive models (Satz, 1993; Stern, 2002) maintain that in response to similar levels of neurobiological degradation, high-reserve individuals will experience less impairment than low-reserve individuals. Resilience of nervous system functioning is theoretically indexed by brain size or synapse count, although Satz (1993) has proposed that education may be an appropriate proxy. Such models often postulate the presence of a neuropathological threshold that is higher for high-reserve people, beyond which cognitive impairment begins to take place. These models therefore predict that the rate of cognitive decline will be slower, or at least delayed, for high-reserve individuals who have not yet reached their neuropathological threshold, even if their rate of neurobiological degradation is comparable to that of low-reserve individuals. However, this view is problematic for examining normal age-associated declines because it is very clear that age-related effects on cognitive performance begin in early adulthood and are continuous rather than abrupt (Salthouse, 2004). A continuum-based passive model might instead predict that high-reserve individuals respond to neurobiological degradation to a lesser extent than do lower reserve individuals (i.e., differential preservation). However, some passive models (cf. Stern, 2002, Figure 3), are difficult to distinguish from functional threshold models.

According to functional threshold models, high- and low-reserve individuals experience similar rates of cognitive decline. However, low-reserve individuals begin adulthood with lower levels of cognitive performance and therefore take less time to drop below a threshold beyond which their level of functioning is considered clinically severe or pathological. These models explain that findings linking reserve markers, such as education, with reduced prevalence and incidence of dementia may be artifacts of arbitrary clinical cutoffs. Although such models have not been discussed in great detail in the cognitive reserve literature, they are consistent with the diagnostic thresholds discussed by Stern (2002) and the diagnostic criteria for various dementias described in the *Diagnostic and Statistical Manual of Mental Disorders* (IV-TR; American Psychiatric Association, 2000).

Potential Artifacts in Change Research: Level–Slope Relations

Variables purported to index cognitive reserve tend to be correlated with levels of cognitive functioning. This is, in fact, a necessary requirement of functional threshold models as described above. If, however, relations exist between levels of functioning and rates of age-associated declines in functioning (i.e., level–slope relations), such phenomena are potentially critical confounds with respect to moderation hypotheses.

There are both methodological and theoretical reasons to expect level–slope relations to exist. In cases of poor instrument sensitivity, ceiling effects can prevent detection of changes within the upper levels of functioning, and floor effects can prevent detection of changes within the lower levels of functioning, thus resulting in spurious relations between initial performance and change. This is of particular relevance to cognitive reserve research, in which many of the measures used are known to have low measurement ceilings (e.g., the MMSE and verbal-learning tests; see, respectively, Anstey & Christensen, 2000; Uttl, 2005). Similar artifacts can occur with respect to the regression to the mean phenomenon (Campbell & Kenny, 1999; Nesselroade, Stigler, & Baltes, 1980). In such cases, subjects scoring at the extremes as the result of ordinary statistical noise are likely to score closer to their true, less extreme scores when measured again. This results in spurious negative correlations between initial level and change. From a theoretical standpoint, if there are physical or biological limits to the upper and lower ends of functioning, then changes toward these extremes will be smaller in magnitude than changes toward the mean, regardless of instrument sensitivity (Ackerman, 2005; Wilder, 1967, the law of initial values).

Method

The current study seeks to test the specificity of the relation between popularly hypothesized cognitive reserve variables (years of educational attainment and vocabulary knowledge) and levels of reasoning and speed performance (intercepts) and rates of longitudinal changes in reasoning and speed performance (slopes) in cognitively normal older adults. In contrast to most examinations of cognitive reserve moderation hypotheses, the longitudinal analyses presented in this study examine the degree to which cognitive reserve variables are related to maturational changes in conjunction with and independently of initial levels of performance. Moreover, we examine maturational decline as a component separate from that associated with the benefits of cumulative test experience (retest effects) associated with repeated assessments.

Advanced Cognitive Training for Independent and Vital Elderly (ACTIVE)

The ACTIVE study is an ongoing randomized controlled trial conducted at six field sites, with the New England Research Institutes as the coordinating center. The primary goal of the trial is to test the effects of three distinct cognitive training interventions on cognitive function and cognitively demanding everyday functioning. This was achieved by random assignment of individuals to one of three active treatment conditions or a no-contact control condition. In these analyses, we use data only from persons enrolled in the control condition. Persons in the active treatment conditions were omitted. No-contact control data from baseline, 12-week posttest, first annual, second annual, third annual, and fifth annual assessments were analyzed. For more detail on design, see Jobe et al. (2001), Ball et al. (2002), and Willis et al. (2006).

Participants

ACTIVE participants were recruited from a number of different settings, registries, and rosters (e.g., state driver's license and identification card registries, medical clinical rosters, senior center and community organization rosters, congregate senior housing sites, local churches, and rosters of assistance and service programs for low-income older persons) with the goal of enrolling a diverse sample of older adults who were living independently and in good functional and cognitive status but at risk for loss of functional independence. Recruitment was focused on six metropolitan areas in the United States. Participants considered for the current analyses were 704 persons age 65–94 years at baseline assessment who were randomly assigned to a no-contact control group from a parent sample of 2,832 persons. Six participants were excluded due to protocol violations.

Table 1 reports the number of participants in each 5-year age group present at each testing occasion. Because only 8 participants were age 90 years or older at baseline assessment, they were excluded from analyses. This exclusion was necessary because of the multiple-age-group accelerated longitudinal design implemented in the analysis. This resulted in a working sample of $N =$ 690 (74% women) at baseline assessment with a 5-year, six-occasion retention rate of 54% (77% women). Reasons for dropout included death, withdrawal, site decision, and unavailability. Scores on the MMSE (Folstein, Folstein, & McHugh, 1975) ranged from 23 to 30 (the means for each age group ranged from 26.7 to 27.6, with standard deviations ranging from 1.8 to 2.1; models excluding participants with MMSE scores less than 25 did not change the patterns of results). Twenty-eight percent of participants were non-White.

Education ranged from 6 to 20 years ($M = 13.4$, $SD = 2.7$). Although negative in magnitude, the absolute value of the age–education correlation was less than 0.1, suggesting a nearly uniform level of selectivity across the age range. Corrections for cohort differences in education (cf. Rönnlund & Nilsson, 2006) produced very similar patterns of results to those reported in this article.

Figure 1 depicts the distributions of years of education across individuals in each 5-year age group. It can be seen that all age groups contained individuals with an education ranging from less than a high school education to greater than a college education, with the largest proportion of individuals having a complete high school or partial college education. Although no groups contained large proportions of participants with very low education (i.e., less than high school), this can be viewed as a strength, because deprivation of basic schooling is likely to be accompanied by other extreme environmental deficiencies that could confound results.

The consequences of this sample's positive selection of well-educated participants were considered in some detail. In particular, it is possible that increments in educational attainment have diminishing returns, such that the difference between having versus not having a high school education has much greater cognitive consequences than the difference between having versus not having a college education. There was some evidence for this, as a significant quadratic trend (producing the above-described pattern) was present in the regression predicting vocabulary knowledge from years of education. However, the size of this effect was very small (the increment in R^2 was .018). Moreover, when an Education^2 term was included in the models, and when the models were fit to low- and high-education groups separately (split at Education ≤ 12 and Education > 12), the results were very similar to those reported here.

Table 1
Sample Size by Age Group and Assessment

Age group (years)	Baseline	Posttest	Annual 1	Annual 2	Annual 3	Annual 5
65–69	182	163	138	130	126	108
70–74	223	202	172	169	155	134
75–79	156	149	124	110	100	86
80–84	92	82	63	54	39	30
85–89	37	36	30	27	23	15
Total	690	632	527	490	443	373

For additional information on sample characteristics and recruiting procedures, see Ball et al. (2002).

Measures

Measures were selected because they were deemed sensitive enough at the upper ranges of performance to detect potential gains of training interventions and at the lower ranges of performance to detect declines associated with late-life aging (Ball et al., 2002).

Reasoning measures required participants to identify patterns in letter or word series problems. The measures were Word Series (Gonda & Schaie, 1985), Letter Series (Thurstone & Thurstone, 1949), and Letter Sets (Ekstrom, French, Harman, & Derman, 1976).

Processing speed measures were timed and required participants to identify and localize information at 75% accuracy under varying levels of cognitive demand. They involved three tasks from the useful field-of-view measure (Owsley, McGwin, & Ball, 1998).

The vocabulary measure (Ekstrom et al., 1976) tested participants' abilities to choose the best synonym for a target word from a number of alternatives.

Equally weighted composite test scores representing reasoning and speed were created by pooling all scores for all participants in the parent population and applying a Blom transformation (Blom, 1958) to make them more normally distributed, as in Ball et al. (2002). To facilitate interpretation, reasoning composite, speed composite, and vocabulary scores were each then standardized with respect to the baseline scores for the youngest age group through a T score metric ($M = 50$, $SD = 10$). All scores were scaled such that higher values indicate superior performance (i.e., the speed composite was reversed).

Analyses and Results

In the following section, we present analyses and results directly relevant to cognitive reserve hypotheses. To allow for lenient tests of cognitive reserve moderation (differential preservation) hypotheses, alpha levels were set to .05.

Cross-Sectional Analyses

If it is the case that higher levels in variables hypothesized to index cognitive reserve, such as education and knowledge, are related to shallower rates of cognitive decline, then one should expect cross-sectional differences in cognitive performance between individuals differing in their levels on those variables to be larger at older ages. This was tested by examining Age × Education and Age × Baseline Vocabulary Knowledge interactions in regressions predicting baseline speed and reasoning performance. In all such regressions, age, education, and vocabulary knowledge were centered by subtracting their means.

Age × Education interactions were examined through hierarchical regressions, with age and education entered in the first step and product of Age × Education entered in the second step. Consistent with the preserved differentiation hypothesis but inconsistent with the differential preservation hypothesis, age and education significantly accounted for both reasoning and speed performance but the Age × Education interaction did not.

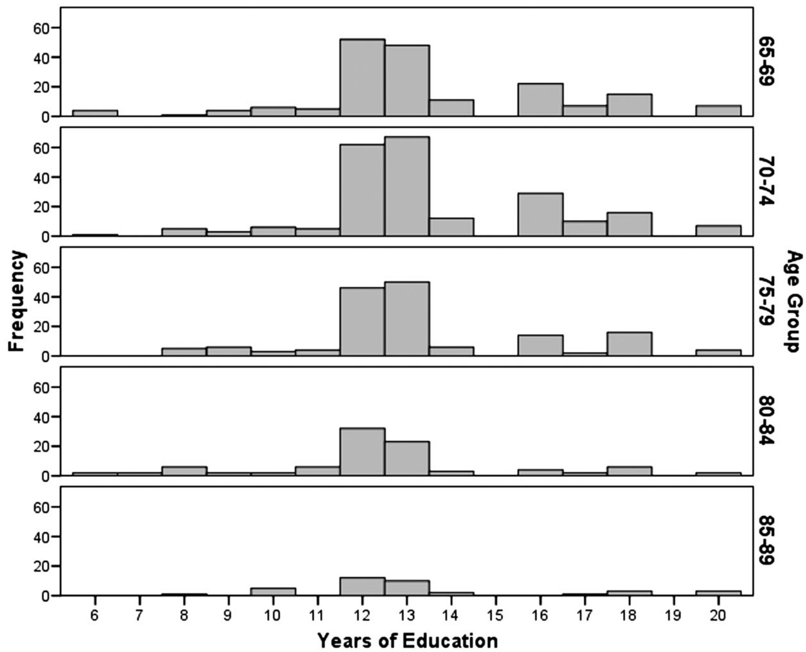

Figure 1. Distribution of education by age group.

In examining Age × Vocabulary Knowledge interactions, vocabulary and age were entered in the first step and the product of Vocabulary × Age was entered in the second step, of hierarchical regressions predicting reasoning and speed. Both regressions resulted in interaction terms that were statistically significant but in the direction opposite to that predicted by cognitive reserve moderation hypotheses. Figure 2 demonstrates these findings, with higher vocabulary individuals exhibiting larger age differences than lower vocabulary individuals.

Longitudinal Analyses

Hypotheses concerning age-related longitudinal changes in reasoning and speed abilities were examined through latent growth curve modeling (LGM) techniques, which are employed through the structural equation modeling framework. LGM techniques are similar to mixed effects or hierarchical modeling techniques in that they allow for the estimation of fixed effects, in the form of population-level growth parameters, and random effects, in the form of individual differences in growth parameters. Individual differences in variables representing these parameters can then be further examined by regressing them onto exogenous variables, such as education or vocabulary.

For the current analyses, we considered a number of alternative time-based, age-based, and occasion-based growth curve models (see Appendix for a discussion of the strengths and weaknesses of each of these models and their results). Here we

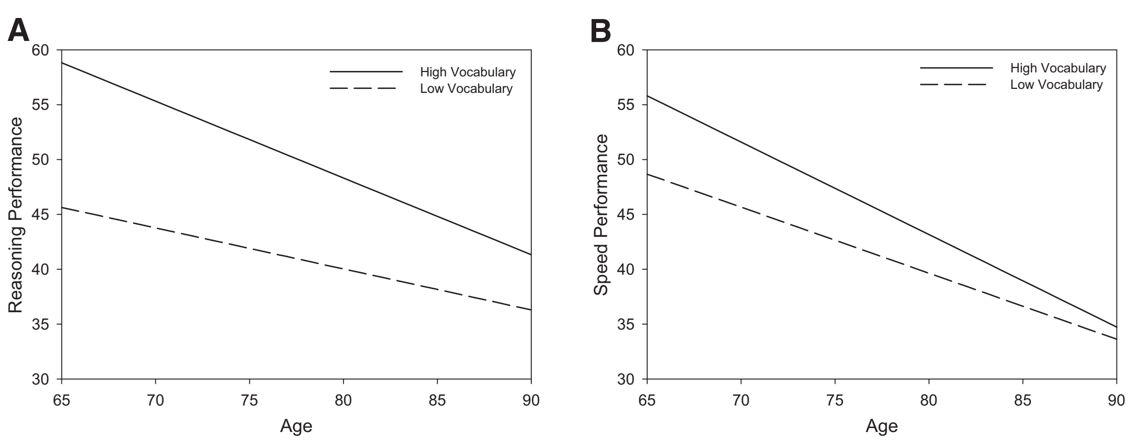

Figure 2. (A) Plot of Age × Vocabulary interaction predicting cross-sectional reasoning performance. (B) Plot of Age × Vocabulary interaction predicting cross-sectional speed performance. In both plots, high and low vocabulary are at one standard deviation above the mean and one standard deviation below the mean, respectively.

report a version of the multiple-group accelerated latent growth curve model (cf. Duncan, Duncan, Strycker, Li, & Alpert, 1999, chapter 6) allowing for retest effects (McArdle & Woodcock, 1997). This model was chosen because (a) retest effects can be maximally separated from maturational change by scaling retest effects by occasions of test experience but scaling maturational change by approximate age at testing; (b) the extent to which the quality of change and predictors of change differ across age groups can be formally tested; (c) the models can be fit with conventional structural equation modeling methods, allowing for detailed fit indices, estimation of indirect effects with standard errors, and, for ease of interpretation, standardized parameter estimates. We note, however, that the substantive conclusions drawn regarding the cognitive reserve hypothesis were the same for all models considered.

The multiple-group accelerated latent growth curve model is schematically depicted in Figure 3. In this diagram, squares represent observed variables, such as scores at each measurement occasion, and circles represent latent or unobserved variables, such as those corresponding to maturational slope (s), intercept (i), and retest effects (r). Regression coefficients are represented as one-headed arrows, and the variance terms of variables, or their residuals, are represented as two-headed arrows attached to the specific variables. The unit constant (allowing for the estimation of means) is represented as a triangle.

The model depicted in Figure 3 fits a similar six-occasion model to each age group (5-year cohort) individually, and across-groups equality constraints are placed on the latent means, latent variances, covariance and regression relations, and residual variances. Some of these constraints can then be removed and the resulting chi-square and degrees-of-freedom change documented to test for between-groups differences. By parameterizing the basis coefficients for the latent slope to reflect cohort age (centered at 65 years), mean age-related change in cognitive functioning is assumed to be linear and reflected by cross-sectional age differences (the convergence assumption; Bell, 1953), while still allowing for individual differences in change to be determined by longitudinal information from repeated measurements. The basis coefficients defining the shape of the retest curve can then be freely estimated from the data. The basis coefficients defining the growth curve intercept are all fixed to 1, allowing the intercept to be interpreted as performance at 65 years of age. Residual variances are all constrained to be equal, reflecting the assumption of homoscedasticity over time.

The growth curve portion of the model depicted in Figure 3 can be expressed as

$$Y[o]_n = i_n + Age[o]_g \times s_n + B[o] \times r_n + u[o]_n, \qquad (1)$$

or in expanded form as

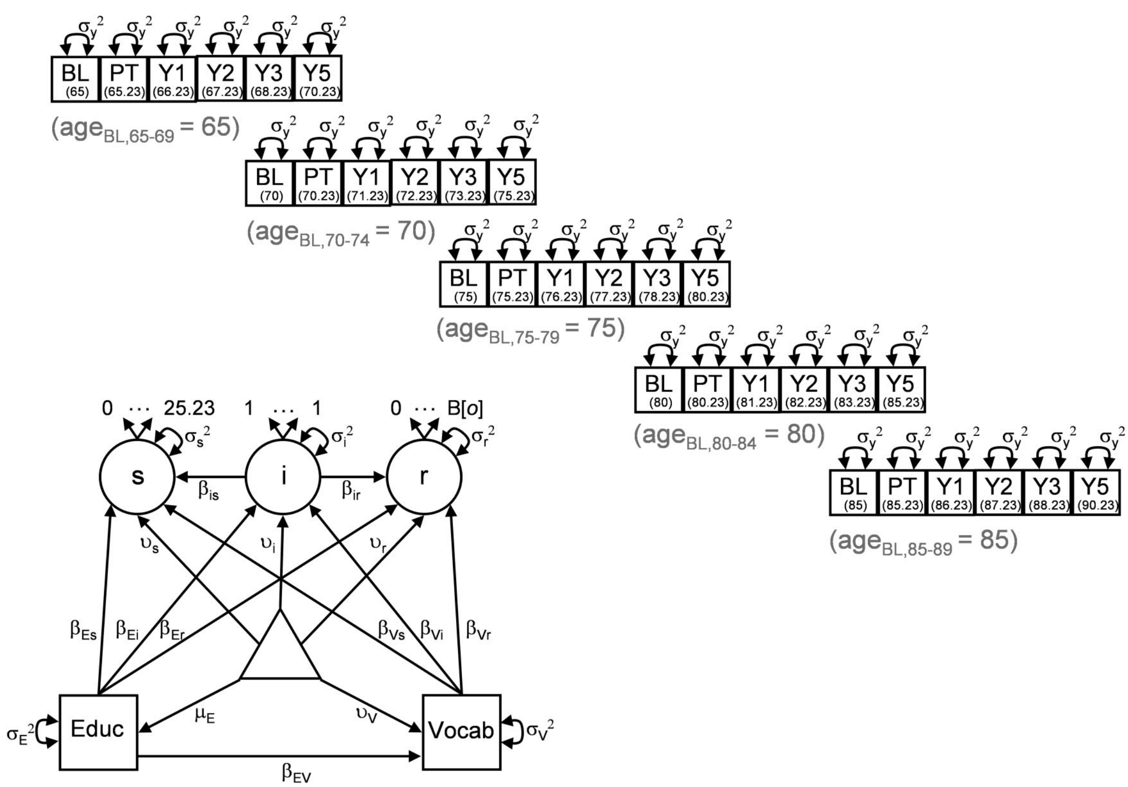

Figure 3. Path diagram depicting the multiple-group accelerated latent growth curve model employed. BL, PT, Y1, Y2, Y3, and Y5 represent vocabulary or speed performance at baseline, 12-week posttest, first annual, second annual, third annual, and fifth annual assessments, respectively. Beneath these labels are the designated ages of each age group at each occasion. Educ = education; vocab = vocabulary; s = maturational slope; i = intercept; r = retest effects.

$$\begin{bmatrix} Y[BL]_n \\ Y[PT]_n \\ Y[1]_n \\ Y[2]_n \\ Y[3]_n \\ Y[5]_n \end{bmatrix} = \begin{bmatrix} 1 & age_{BL,g} - 65.00 & 0 \\ 1 & age_{BL,g} - 64.77 & 1 \\ 1 & age_{BL,g} - 63.77 & B[1] \\ 1 & age_{BL,g} - 62.77 & B[2] \\ 1 & age_{BL,g} - 61.77 & B[3] \\ 1 & age_{BL,g} - 59.77 & B[5] \end{bmatrix} \begin{bmatrix} i_n \\ s_n \\ r_n \end{bmatrix} + \begin{bmatrix} u[BL]_n \\ u[PT]_n \\ u[1]_n \\ u[2]_n \\ u[3]_n \\ u[5]_n \end{bmatrix},$$

where g indicates that a variable is group specific and n indicates that a variable varies across individuals. $\text{Age}_{BL,g}$ represents the designated age (in years) of age group g at baseline assessment ($\text{Age}[o]_g$ therefore corresponds to the designated age of the group at any given occasion, centered at 65 years). Equation 1 explains that individual scores at each measurement occasion $Y[o]_n$ can be fully accounted for by individual differences in growth curve intercept (i_n), maturational slope (s_n), retest effects (r_n), and unexplained variance ($u[o]_n$).

Growth curve intercept, slope, and retest effects are regressed onto education and baseline vocabulary knowledge (both education and vocabulary were centered at their means for each age group, such that $\mu_E = 0$ and $\upsilon_V = 0$) according to the following equations:

$$i_n = \upsilon_i + \beta_{Ei} \times (\text{Education}_n) + \beta_{Vi} \times (\text{Vocabulary}_n) + e1_n, \quad (2)$$

$$s_n = \upsilon_s + \beta_{is} \times (i_n) + \beta_{Es} \times (\text{Education}_n) + \beta_{Vs} \times (\text{Vocabulary}_n) + e2_n, \quad (3)$$

and

$$r_n = \upsilon_r + \beta_{ir} \times (i_n) + \beta_{Er} \times (\text{Education}_n) + \beta_{Vr} \times (\text{Vocabulary}_n) + e3_n, \quad (4)$$

where υ represents regression intercepts, β represents regression coefficients, and e represents residuals. These equations allow for identification of relations between individual growth curve parameters and hypothesized cognitive reserve variables. Note that growth curve slope and retest effects are regressed onto the growth curve intercept to determine the degree to which relations are mediated through initial performance and the degree to which relations are independent of initial performance. Finally, vocabulary is regressed onto education according to

$$\text{Vocabulary}_n = \upsilon_V + \beta_{EV} \times (\text{Education}_n) + e4_n, \quad (5)$$

under the assumption that vocabulary knowledge is, in part, the product of education. To account for the possibility that, as a result of social inequalities, years of education may have different meaning for men and women, and Whites and non-Whites (Manly et al., 2003), models were considered in which variables representing gender and race were included as covariates in Equations 2–5. This addition did not change the overall pattern of results or the substantive interpretations drawn. We therefore report the simpler models.

All LGM analyses were conducted through the Mplus software package (Muthén & Muthén, 2006) with full information maximum likelihood (FIML) estimation methods. FIML estimates parameter values on the basis of all available data, under the missing-at-random (MAR) assumption that any systematic patterns of missingness are functions of the variables included in the model and that the patterns of and predictors of growth and change are the same for complete and incomplete subgroups. Longitudinal growth curve methods employing the MAR assumption to handle selective attrition have been successfully applied to simulated data (e.g., McArdle & Hamagami, 1992) and are regularly applied to real data (e.g., Ferrer, Salthouse, McArdle, Stewart, & Schwartz, 2005; McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002). In the current study, attrition analyses indicated that those who were lower performing on cognitive measures at baseline were more likely to drop out of the study but that neither education nor vocabulary knowledge was related to study dropout. Moreover, models fit to data from participants with complete data on all six measurement occasions produced similar patterns of results to those reported here. Therefore, although the MAR assumption remains untestable, these follow-up analyses suggest that the substantive findings are robust.

Table 2 reports fit statistics for the unconditional reasoning and speed growth curve models, with the mean retest effect and retest curve shape constrained to be equal across age groups, the mean retest effect allowed to differ across age groups, and the

Table 2
Model Fit Comparisons: Unconditional Models

Model	χ^2	*df*	CFI	TLI	AIC	BIC	RMSEA	$\Delta\chi^2$	Δdf	*p* of Δ
Reasoning										
Fully constrained	163.019	121	.990	.994	18186.253	18249.766	.053		baseline	
Free retest mean	155.239	117	.991	.994	18186.472	18268.132	.049	7.78	4	>.05
Free retest mean and shape	**126.101**	**101**	**.994**	**.996**	**18189.335**	**18343.582**	**.042**	**29.138**	**16**	**<.05**
Speed										
Fully constrained	189.688	121	.969	.981	20329.851	20393.303	.064		baseline	
Free retest mean	**167.514**	**117**	**.977**	**.985**	**20315.677**	**20397.259**	**.056**	**22.174**	**4**	**<.001**
Free retest mean and shape	148.728	101	.978	.984	20328.890	20482.990	.059	18.786	16	>.05

Note. The best-fitting models are in bold. CFI = comparative fit index; TLI = Tucker–Lewis index; AIC = Akaike information criterion; BIC = Bayesian information criterion; RMSEA = root-mean-square error of approximation.

mean retest effect and retest curve shape allowed to differ across age groups. Because these models were nested within one another, chi-square difference tests were used to select models. It can be seen that the preferred reasoning model was one in which the mean and shape of the retest curve was allowed to differ among the age groups, whereas the preferred speed model was one in which the shape of the retest curve was invariant across age groups but the mean retest effect was allowed to differ across age groups.

Figures 4 and 5 depict maturational components, retest components, and net trajectory of the population average growth curves implied by the reasoning and speed models, respectively. It can be seen that for both reasoning and speed, the largest retest benefit occurs during the first retesting, and the younger groups tend to benefit more than the older groups. Moreover, maturational age gradients for speed ($-.70$ T score units per year, $p < .05$) were considerably steeper ($p_{\mathrm{difference}} < .05$) than for reasoning ($-.49$ T score units per year, $p < .05$).

Table 3 reports the fit statistics for the reasoning and speed growth curve models (the best-fitting reasoning and speed models selected from Table 2), with the relations (β_{Es}, β_{Er}, β_{vs}, and β_{vr} from Equations 2–5 and Figure 3) between hypothesized cognitive reserve variables and latent change components held constant across age groups (fully constrained models), and the change in fit after freeing these relations across groups (predictors-freed models). All other parameters in Equations 2–5 were constrained to be constant across groups in both sets of models. The fit statistics indicate well-fitting models, with all root-mean-square errors of approximation less than .07 and all comparative fit indices greater than .96. Because these fully constrained models did not fit significantly worse (by nested chi-square comparison) than the less parsimonious predictors-freed models, we accept them as the best representations of 5-year changes in reasoning and speed performance and their relations with education and vocabulary. The results of these models are described below.

Tables 4 and 5 report the relations between hypothesized cognitive reserve variables and growth curve variables for the reasoning and speed models, respectively. Unstandardized parameter estimates and, for ease of interpretation, standardized parameter estimates are reported. Total effects (the sum of unique and mediated effects), direct (unique) effects, and indirect (mediated) effects are reported. This allows for examinations of the relations between cognitive reserve markers (education and vocabulary) and maturational changes both with and without controlling for the intercepts, as well as the relation that is completely attributable to the intercepts.

A number of observations are of note. First, the intercepts were highly related to both hypothesized cognitive reserve variables (education and vocabulary), but most of the education effect was mediated through vocabulary. Second, maturational slopes were not significantly related to hypothesized cognitive reserve variables, whether the significant influences of the intercepts were controlled for. Third, there were significant negative relations between intercepts and maturational slopes, such that individuals at higher levels of functioning declined more steeply. Finally, for speed, the retest component was positively related to the intercept, but there were no significant direct or total relations between the retest component and hypothesized cognitive reserve variables. For reasoning, there were no significant relations between the retest component and intercepts or the retest component and hypothesized cognitive reserve variables.

Evidence for the Reliability of Change

Finally, we examined whether our failures to detect relations between hypothesized reserve variables and longitudinal cognitive changes (maturational slopes) resulted from failures to assess these changes reliably. The reliable assessment of change has been a long-standing issue in aging research (for a discussion, see Hertzog & Nesselroade, 2003). Hertzog, Linden-

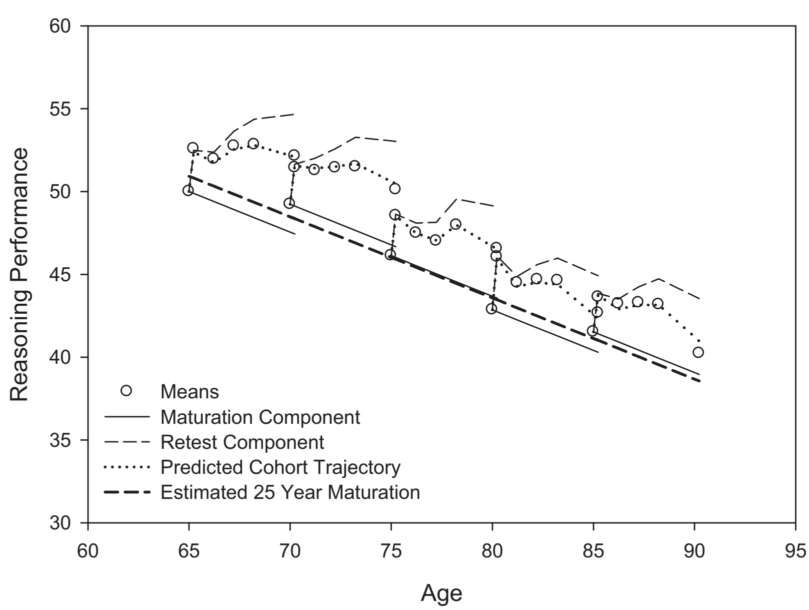

Figure 4. Model-implied population components of 5-year longitudinal changes in reasoning performance.

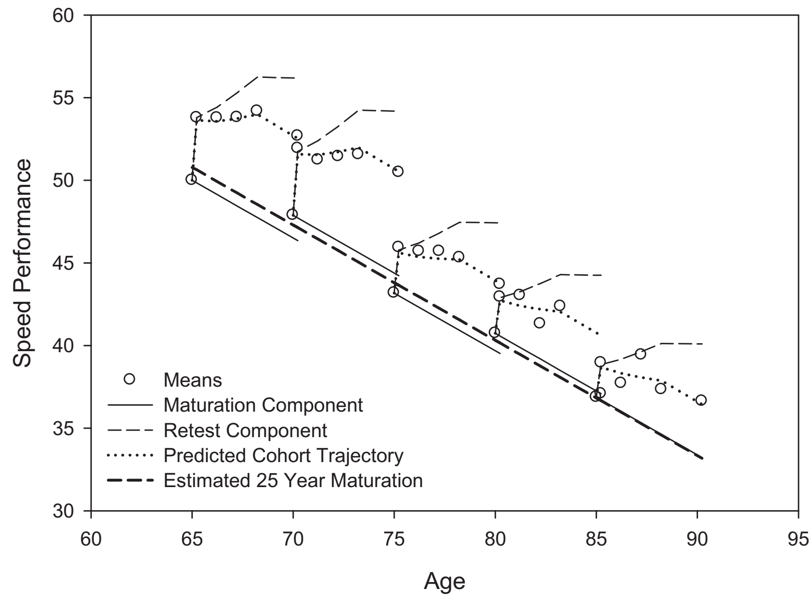

Figure 5. Model-implied population components of 5-year longitudinal changes in speed performance.

berger, Ghisletta, and von Oertzen (2006) have recently called to attention that the extent to which growth curve modeling has the capability to detect correlates of change is still largely unknown, and arguing for the null hypothesis may therefore be problematic. They explain that because growth curve slopes have the most potential to lack reliability, it is particularly difficult to identify correlates of slopes. Following this logic in reverse, we reason that if we are able to detect moderate to large correlations between changes in reasoning and speed, the latent slopes are likely to be sufficiently reliable (and variable) to detect relations with hypothesized reserve variables.

To examine coupled change, the unconditional reasoning and speed models used in the previous analyses were combined into a multiple-group bivariate latent growth curve model (McArdle & Nesselroade, 2003). To maintain consistency with the models reported in Tables 4 and 5, the basis coefficients defining the shape of the retest effects, the variances of the intercepts, and the residual variances of the reasoning and speed scores for each occasion were fixed to the values that had been estimated with those models. To control for the possibility that latent slopes may be related to one another by way of their relations to the intercepts, latent slopes were regressed onto both latent intercepts and their residuals allowed to covary. Similarly, retest components were regressed onto latent intercepts and their residuals allowed to covary. The covariance between the latent intercepts was also estimated. To maintain further consistency with the models previously reported, variance, covariance, and regression parameters were constrained to be equal across age groups.

Parameters for the bivariate growth curve model are presented in Table 6. Consistent with the positive manifold (Spearman, 1927), intercepts were strongly related to one another (r = .626). Moreover, even after controlling for the influences of the latent intercepts, highly significant relations were found between latent maturational slopes (r = .636) but not latent retest components. We therefore conclude that the latent slopes were modeled with sufficient reliability to have detected relations with hypothesized cognitive reserve variables, had they been present. Our failures to detect predictors of retest components, however, may be attributable to failures to assess them reliably (or lack of sufficient individual differences in these components).

Discussion

Summary and Discussion of Findings

In this study, we examined the hypotheses that education and vocabulary knowledge, as markers of cognitive reserve, are (a)

Table 3
Model Fit Comparisons: Conditional Models

Model	χ^2	*df*	CFI	TLI	AIC	BIC	RMSEA	$\Delta\chi^2$	Δdf	*p* of Δ
Reasoning: Fully constrained	**205.092**	**160**	**.991**	**.992**	**26113.245**	**26340.080**	**.045**		baseline	
Reasoning: Predictors freed	187.435	144	.991	.991	26127.588	26427.010	.047	17.657	16	>.05
Speed: Fully constrained	**259.264**	**176**	**.966**	**.973**	**28497.663**	**28651.911**	**.059**		baseline	
Speed: Predictors freed	248.302	160	.964	.968	28518.701	28745.536	.063	10.962	16	>.05

Note. The best-fitting models are in bold. CFI = comparative fit index; TLI = Tucker–Lewis index; AIC = Akaike information criterion; BIC = Bayesian information criterion; RMSEA = root-mean-square error of approximation.

Table 4
Key Parameter Estimates for Reasoning Model (Baseline, Fully Constrained, Model From Table 3)

Parameter	Total effects			Direct effects			Mediated by i and/or vocabulary		
	Parameter estimate	Estimate/*SE*	Standardized parameter estimate	Parameter estimate	Estimate/*SE*	Standardized parameter estimate	Parameter estimate	Estimate/*SE*	Standardized parameter estimate
i on education (β_{ei})	1.464*	10.154*	.455*	0.663*	4.419*	.206*	0.801*	8.778*	.249*
i on vocabulary (β_{vi})	0.473*	11.321*	.518*	0.473*	11.321*	.518*			
s on i (β_{is})	−0.030*	−4.683*	−.668*	−0.030*	−4.683*	−.668*			
s on education (β_{es})	−0.019	−1.481	−.133	0.013	0.995	.090	−0.032*	−3.838*	−.224*
s on vocabulary(β_{vs})	−0.007	−1.753	−.178	0.007	1.539	.167	−0.014*	−4.335*	−.346*
r on education (β_{er})	−0.055	−1.152	−.214	−0.101	−1.848	−.396	0.046	1.613	.182
r on vocabulary (β_{vr})	0.014	0.947	.191	−0.003	−0.145	−.035	0.016	1.591	.226
r on i (β_{ir})	0.035	1.609	.437	0.035	1.609	.437			
vocabulary on education (β_{ev})	1.695*	13.884*	.481*	1.695*	13.884*	.481*			

Note. i = latent growth curve intercept; s = maturational slope; r = retest component.
* $p < .05$.

associated with higher levels of functioning in old age and (b) associated with shallower rates of age-associated declines in functioning, for variables indexing reasoning and speed. We found evidence for the former hypothesis but not for the latter.

Contrary to cognitive reserve theories predicting moderation or differential preservation, both with and without accounting for the mediation of the intercepts, education and vocabulary knowledge were unrelated to rates of maturational decline. These findings suggest that the late-life relations between education and vocabulary, as markers of cognitive reserve, and cognitive functioning reflect the persistence of earlier life differences in cognitive functioning and not differential rates of cognitive decline.

Processing speed, compared with reasoning, showed smaller level relations with education and vocabulary and steeper age gradients, suggesting that processing speed may be a cognitive primitive that is less related to skill or acquired knowledge and more reflective of age-associated neurobiological degradation (cf. Salthouse, 1996). If it is the case that reasoning is more environmentally influenced than speed, and therefore potentially more amenable to protective cognitive reserve processes, one might have expected rates of change in reasoning to show greater positive relations to hypothesized cognitive reserve markers. We found no evidence for this, as neither reasoning nor speed changes were significantly associated with vocabulary or education in the predicted directions.

The relations between education and levels of cognitive performance were substantially mediated by vocabulary knowledge, suggesting that the benefits of education may be best indexed by knowledge measures, for which confounds concerning quality (or yearly value) of education are not of issue (cf. Jones, 2003).

On the basis of these findings, we conclude that cognitive reserve models predicting stability, rather than moderation, of performance differences are most plausible. In cases of active cognitive reserve models, this would mean that rather than rely increasingly on knowledge-based paradigms and brain networks with age, individuals high in knowledge and education rely upon these advantages consistently over their late adult lives. Contrary to the predictions of passive cognitive reserve models, these findings suggest that individuals high in knowledge and education

Table 5
Key Parameter Estimates for Speed Model (Baseline, Fully Constrained, Model From Table 3)

Parameter	Total effects			Direct effects			Mediated by i and/or vocabulary		
	Parameter estimate	Estimate/*SE*	Standardized parameter estimate	Parameter estimate	Estimate/*SE*	Standardized parameter estimate	Parameter estimate	Estimate/*SE*	Standardized parameter estimate
i on education (β_{ei})	0.712*	4.230*	.240*	0.261	1.390	.088	0.451*	4.771*	.152*
i on vocabulary (β_{vi})	0.266*	5.079*	.316*	0.266*	5.079*	.316*			
s on i (β_{is})	−0.020*	−2.515*	−.819*	−0.020*	−2.515*	−.819*			
s on education (β_{es})	−0.009	−0.619	−.127	0.011	0.755	.153	−0.021*	−2.471*	−.280*
s on vocabulary (β_{vs})	−0.009	−1.829	−.431	−0.004	−0.766	−.172	−0.005*	−2.289*	−.259*
r on education (β_{er})	0.029	0.415	.053	−0.054	−0.670	−.098	0.084*	2.012*	.150*
r on vocabulary (β_{vr})	0.037	1.643	.233	0.015	0.635	.095	0.022*	2.192*	.137*
r on i (β_{ir})	0.082*	2.437*	.434*	0.082*	2.437*	.434*			
vocabulary on education (β_{ev})	1.698*	13.900*	.482*	1.698*	13.900*	.482*			

Note. i = latent growth curve intercept; s = maturational slope; r = retest component.
* $p < .05$.

Table 6
Fit Indices and Key Parameter Estimates for Bivariate Latent Growth Model

Parameter	Parameter estimate	Estimate/ *SE*	Standardized parameter estimate
Model fit indices			
χ^2	601.767		
df	423		
CFI	.974		
TLI	.980		
RMSEA	.055		
Parameter estimates			
Reasoning slope on reasoning intercept (s_R on i_R)	-0.027^*	-4.148^*	$-.519^*$
Reasoning slope on speed intercept (s_R on i_S)	-0.003	-0.298	$-.045$
Speed slope on speed intercept (s_S on i_S)	-0.014	-1.606	$-.343$
Speed slope on reasoning intercept (s_S on i_R)	-0.018^*	-2.261^*	$-.467^*$
Reasoning retest on reasoning intercept (r_R on i_R)	-0.016	0.764	.322
Reasoning retest on speed intercept (r_R on i_S)			
Speed retest on speed intercept (r_S on i_S)	0.086^*	2.331^*	$.568^*$
Speed retest on reasoning intercept (r_S on i_R)	-0.008	-0.257	$-.059$
Reasoning intercept with speed intercept (i_R with i_S)	45.734^*	15.178^*	$.626^*$
Reasoning slope with speed slope (s_R with s_S)	0.102^*	4.033^*	$.636^*$
Reasoning retest with speed retest (r_R with r_S)	0.172	0.397	.320

Note. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; i = latent growth curve intercept; s = maturational slope; r = retest component; R = reasoning; S = speed.
* $p < .05$.

exhibit similar degrees of age-associated cognitive decrements as those less knowledgeable and educated.

Consistent with functional threshold predictions, cognitive reserve variables were found to be related to levels of reasoning and speed performance but unrelated to rates of decline in reasoning and speed performance. Prevalence and incidence studies supportive of cognitive reserve may therefore simply be artifacts of arbitrary clinical cutoffs for pathological functioning and dementia. This is because, on average, more highly educated individuals begin adulthood with higher levels of cognitive functioning. Therefore, they take longer to reach clinically significant levels of functioning compared with lower educated individuals whose abilities decline at similar average rates.

Previous studies supportive of cognitive reserve moderation hypotheses may be results of poor psychometric properties of the cognitive measures used, or inappropriate use of the instruments, such as those with pronounced ceiling effects. Although the methods often used assume interval measurement, this is often not the case, particularly at the extremes of the scales (Embretson & Reise, 2000). In the current study, the instruments used were sensitive to a wide range of abilities, and latent intercepts were considered as potential mediators of latent slope relations. In fact, previous investigations (e.g., Christensen et al. 2001; Hofer et al., 2002; Mackinnon et al., 2003) using sensitive measures and sophisticated modeling techniques have also failed to find associates between cognitive reserve markers and rates of change.

Limitations

It is important to acknowledge that this study included participants who were, on the whole, at healthy levels of cognitive functioning. Our findings may therefore be relevant only to the patterns of aging that precede senile dementia but not the patterns ensuing from dementia. Moreover, although there was little evidence that results qualitatively differed for low- and high-education participants (see *Participants* section), very few participants with severely impoverished educational backgrounds (e.g., less than 8 years of education) were included in the sample, and we are therefore unable to make strong generalizations to such populations. It is also possible that cognitive reserve mechanisms may act differently on different abilities (e.g., memory), and we must therefore limit our conclusions to levels and rates of change in reasoning and processing speed, the cognitive outcomes measured in this study. Furthermore, it is important to keep in mind that although popularly examined, educational attainment and measures of acquired knowledge may only be surrogate markers for theoretical constructs hypothesized to protect against cognitive decline. Finally, it is possible that rather than be related to earlier life environmental quality, those factors that truly serve to mitigate late-life cognitive changes themselves emerge during late life. It might therefore be desirable for future examinations of potential moderators of cognitive aging to examine hypothesized cognitive reserve markers that are measured at closer temporal proximities to the senescent changes of interest.

Conclusions

The current study yielded considerable evidence unsupportive of the notion that formal education during earlier life is related to rates of decline in cognitive functioning during later life. However, levels of cognitive performance were substantially related to levels of educational attainment, as well as to vocabulary knowledge, a likely product of educational achievement. Therefore, to the extent that education causally influences cognitive abilities during childhood development (Ceci, 1996), these benefits seem to persist throughout the lifespan and until late adulthood (Deary, Whalley, Lemmon, Crawford, & Starr, 2000). The persistence of such benefits may also serve to protect against functional impairment (as described by functional threshold models) and therefore have substantial implications for everyday functioning in later life.

These findings argue for an integrated approach to developmental psychology that continues to emphasize both early-life and late-life phenomena (Baltes, 1987; Craik & Bialystok, 2006). Developing a fuller understanding of the education–cognition relation in late life certainly requires further untangling of the causal components of the education–cognition relation during childhood and determination of the effects of continuing education and cognitive training (e.g., Willis et al., 2006) during adulthood. Moreover, research focusing on lifespan longitudinal data (e.g., Deary et al., 2000; McArdle et al., 2002) will continue to prove useful in better understanding and characterizing the processes of change that occur within individuals as they grow and mature.

References

Ackerman, P. L. (2005). Ability determinants of individual differences in skilled performance. In R. J. Sternberg & J. Pretz (Eds.), *Cognition and intelligence: Identifying the mechanisms of the mind* (pp. 142–159). New York: Cambridge University Press.

American Psychiatric Association. (2000). *Diagnostic and statistical manual of mental disorders* (4th ed., text rev.). Washington, DC: Author.

Andel, R., Vigen, C., Mack, W. J., Clark, L., & Gatz, M. (2006). The effect of education and occupational complexity on rate of cognitive decline in Alzheimer's patients. *Journal of the International Neuropsychological Society, 12,* 147–152.

Anstey, K., & Christensen, H. (2000). Education, activity, health, blood pressure and apolipoprotein E as predictors of cognitive change in older age: A review. *Gerontology, 46,* 163–177.

Ball, K., Berch, D. B., Helmers, K. F., Jobe, J. B., Leveck, M. D., Marsiske, M., et al. (2002, November). Effects of cognitive training interventions with older adults: A randomized controlled trial. *Journal of the American Medical Association, 288,* 2271–2281.

Baltes, P. B. (1987). Theoretical propositions of life-span developmental psychology: On the dynamics between growth and decline. *Developmental Psychology, 23,* 611–626.

Bell, R. Q. (1953). Convergence: An accelerated longitudinal approach. *Child Development, 24,* 145–152.

Blom, G. (1958). *Statistical estimates and transformed beta variables.* New York: Wiley.

Bosma, H., van Boxtel, M. P. J., Ponds, R. W. H. M., Houx, P. J. H., & Jolles, J. (2003). Education and age-related cognitive decline: The contribution of mental workload. *Educational Gerontology, 29,* 165–173.

Campbell, D. T., & Kenny, D. A. (1999). *A primer on regression artifacts.* New York: Guilford.

The Canadian Study of Health and Aging. (1994). Risk factors for Alzheimer's disease in Canada. *Neurology, 44,* 2073–2080.

Ceci, S. J. (1996). *On intelligence: A bio-ecological treatise on intellectual development* (2nd ed.). Cambridge, MA: Harvard University Press.

Christensen, H., Anstey, K. J., Leach, L. S., & Mackinnon, A. J. (2008). Intelligence, education, and the brain reserve hypothesis. In F. I. M. Craik & T. A. Salthouse (Eds.), *The handbook of aging and cognition* (3rd ed.). Hillsdale, NJ: Erlbaum.

Christensen, H., Hofer, S. M., Mackinnon, A. J., Korten, A. E., Jorm, A. F., & Henderson, A. S. (2001). Age is no kinder to the better educated: Absence of an association established using latent growth techniques in a community sample. *Psychological Medicine, 31,* 15–27.

Craik, F. I. M., & Bialystok, E. (2006). On structure and process in lifespan cognitive development. In E. Bialystock & F. I. M. Craik (Eds.), *Lifespan cognition: Mechanisms of change* (pp. 3–13). New York: Oxford University Press.

Crano, W. D., Kenny, D. A., & Campbell, D. T. (1972). Does intelligence cause achievement? A cross-lagged panel analysis. *Journal of Educational Psychology, 63,* 258–275.

Deary, I. A., Whalley, L. J., Lemmon, H., Crawford, J. R., & Starr, J. M. (2000). The stability of individual differences in mental ability from childhood to old age: Follow-up of the 1932 Scottish Mental Survey. *Intelligence, 28,* 49–55.

Dickens, W. T., & Flynn, J. R. (2001). Heritability estimates versus large environmental effects: The IQ paradox resolved. *Psychological Review, 108,* 356–369.

Duncan, T. E., Duncan, S. C., Strycker, L. A., Li, F., & Alpert, A. (1999). *An introduction to latent variable growth curve modeling.* Mahwah, NJ: Erlbaum.

Ekstrom, R. B., French, J. W., Harman, H., & Derman, D. (1976). *Kit of factor-referenced cognitive tests* (rev. ed.). Princeton, NJ: Educational Testing Service.

Embretson, S. E., & Reise, S. (2000). *Item response theory for psychologists.* Mahwah, NJ: Erlbaum.

Ferrer, E., Salthouse, T. A., McArdle, J. J., Stewart, W. F., & Schwartz, B. S. (2005). Multivariate modeling of age and retest in longitudinal studies of cognitive abilities. *Psychology and Aging, 20,* 412–422.

Folstein, M. F., Folstein, S. E., & McHugh, P. R. (1975). "Mini-Mental State": A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research, 12*(3), 189–198.

Ghisletta, P., & de Ribaupierre, A. (2005). A dynamic investigation of cognitive dedifferentiation with control for retest: Evidence from the Swiss Interdisciplinary Longitudinal Study on the Oldest Old. *Psychology and Aging, 20,* 671–682.

Ghisletta, P., & Lindenberger, U. (2003). Age-based structural dynamics between perceptual speed and knowledge in the Berlin Aging Study: Direct evidence for ability dedifferentiation in old age. *Psychology and Aging, 18,* 696–713.

Ghisletta, P., & Lindenberger, U. (2004). Static and dynamic longitudinal structural analyses of cognitive changes in old age. *Gerontology, 50,* 12–16.

Gonda, J., & Schaie, K. W. (1985). *Schaie-Thurstone Mental Abilities Test: Word Series Test.* Palo Alto, CA: Consulting Psychologists Press.

Hertzog, C., Lindenberger, U., Ghisletta, P., & von Oertzen, T. (2006). On the power of multivariate latent growth curve models to detect correlated change. *Psychological Methods, 11*(3), 244–252.

Hertzog, C., & Nesselroade, J. R. (2003). Assessing psychological change in adulthood: An overview of methodological issues. *Psychology and Aging, 18,* 639–657.

Hofer, S. M., Christensen, H., MacKinnon, A. J., Korten, A. E., Jorm, A. F., Henderson, A. S., & Easteal, S. (2002). Change in cognitive functioning associated with apoE genotype in a community sample of older adults. *Psychology and Aging, 17,* 194–208.

Jensen, A. R. (1998). *The* g *factor: The science of mental ability.* Westport, CT: Praeger/Greenwood.

Jobe, J. B., Smith, D. M., Ball, K., Tennstedt, S. L., Marsiske, M., Willis, S. L., et al. (2001). ACTIVE: A cognitive intervention trial to promote independence in older adults. *Controlled Clinical Trials, 22,* 453–479.

Jones, R. N. (2003). Racial bias in the assessment of cognitive functioning of older adults. *Aging and Mental Health, 7,* 83–102.

Lyketsos, C. G., Chen, L. S., & Anthony, J. C. (1999). Cognitive decline in adulthood: An 11.5-year follow-up of the Baltimore Epidemiologic Catchment Area Study. *American Journal of Psychiatry, 156,* 58–65.

Mackinnon, A., Christensen, H., Hofer, S. M., Korten, A., & Jorm, A. F. (2003). Use it and still lose it? The association between activity and cognitive performance established using latent growth techniques in a community sample. *Aging, Neuropsychology, and Cognition, 10,* 215–229.

Manly, J. J., Touradji, P., Tang, M. X., & Stern, Y. (2003). Literacy and memory decline among ethnically diverse elders. *Journal of Clinical and Experimental Neuropsychology, 25,* 680–690.

McArdle, J. J., Ferrer-Caja, E., Hamagami, F., & Woodcock, R. W. (2002). Comparative longitudinal structural analyses of growth and decline of multiple intellectual abilities over the lifespan. *Developmental Psychology, 38,* 115–142.

McArdle, J. J., & Hamagami, E. (1992). Modeling incomplete longitudinal and cross-sectional data using latent growth structural models. *Experimental Aging Research, 18,* 145–166.

McArdle, J. J., & Nesselroade, J. R. (2003). Growth curve analyses in contemporary psychological research. In J. Schinka & W. Velicer (Eds.), *Comprehensive handbook of psychology: Vol. 2. Research methods in psychology* (pp. 447–480). New York: Pergamon.

McArdle, J. J., & Woodcock, J. R. (1997). Expanding test-rest designs to include developmental time-lag components. *Psychological Methods, 2,* 403–435.

Muthén, L. K., & Muthén, B. O. (2006). *Mplus user's guide* (4th ed.). Los Angeles: Author.

Nesselroade, J. R., Stigler, S. M., & Baltes, P. B. (1980). Regression toward the mean and the study of change. *Psychological Bulletin, 88,* 622–637.

Owsley, C., McGwin, G., Jr., & Ball, K. (1998). Vision impairment, eye disease, and injurious motor vehicle crashes in the elderly. *Ophthalmic Epidemiology, 5,* 101–113.

Rönnlund, M., & Nilsson, L.-G. (2006). Adult life-span patterns in WAIS-R Block Design performance: Cross-sectional versus longitudinal age gradients and relations to demographic factors. *Intelligence, 34,* 63–78.

Salthouse, T. A. (1991). *Theoretical perspectives on cognitive aging.* Hillsdale, NJ: Erlbaum.

Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review, 103,* 403–428.

Salthouse, T. A. (2003). Interrelations of aging, knowledge, and cognitive performance. In U. Staudinger & U. Lindenberger (Eds.), *Understanding human development: Dialogues with lifespan psychology* (pp. 265–287). Berlin, Germany: Kluwer Academic.

Salthouse, T. A. (2004). What and when of cognitive aging. *Current Directions in Psychological Science, 13,* 140–144.

Salthouse, T. A. (2006). Mental exercise and mental aging: Evaluating the validity of the "use it or lose it" hypothesis. *Perspectives on Psychological Science, 1,* 68–87.

Salthouse, T. A., Babcock, R. L., Skovronek, E., Mitchell, D. R. D., & Palmon, R. (1990). Age and experience effects in spatial visualization. *Developmental Psychology, 26,* 128–136.

Satz, P. (1993). Brain reserve capacity on symptom onset after brain injury: A formulation and review of evidence for threshold theory. *Neuropsychology, 7,* 273–295.

Snowdon, D. A., Kemper, S. J., Mortimer, J. A., Greiner, L. H., Wekstein, D. R., & Markesbery, W. R. (1996, February). Linguistic ability in early life and cognitive function and Alzheimer's disease in late life. Findings from the Nun Study. *Journal of the American Medical Association, 21,* 528–532.

Spearman, C. (1927). *The abilities of man: Their nature and measurement.* New York: Macmillan.

Stern, Y. (2002). What is cognitive reserve? Theory and research application of the reserve concept. *Journal of the International Neuropsychological Society, 8,* 448–460.

Stern, Y., Albert, S., Tang, M.-X., & Tsai, W.-Y. (1999). Rate of memory decline in AD is related to education and occupation: Cognitive reserve? *Neurology, 53,* 1942–1947.

Sternberg, R. J., & Gringorenko, E. (Eds.). (1997). *Intelligence, heredity, and environment.* New York: Cambridge University Press.

Teri, L., McCurry, S. M., Edland, S. D., Kukull, W. A., & Larson, E. B. (1995). Cognitive decline in Alzheimer's disease: A longitudinal investigation of risk factors for accelerated decline. *Journals of Gerontology: Biological Sciences and Medical Sciences, 50*A, M49–M55.

Thurstone, L. L., & Thurstone, T. G. (1949). *Examiner manual for the SRA Primary Mental Abilities Test (Form 10–14).* Chicago: Science Research.

Unverzagt, F. W., Hui, S. L., Farlow, M. R., Hall, K. S., & Hendrie, H. C. (1998). Cognitive decline and education in mild dementia. *Neurology, 50,* 181–185.

Uttl, B. (2005). Measurement of individual differences: Lessons from memory assessment in research and clinical practice. *Psychological Science, 16,* 460–467.

Valenzuela, M. J., & Sachdev, P. (2006). Brain reserve and dementia: A systematic review. *Psychological Medicine, 36,* 441–454.

Whalley, L. J., Starr, J. M., Athawes, R., Hunter, D., Pattie, A., & Deary, I. J. (2000). Childhood mental ability and dementia. *Neurology, 55,* 1455–1459.

Wilder, J. (1967). *Stimulus and response. The law of initial values.* Bristol, England: John Wright & Sons.

Willis, S. L., Tennstedt, S. L., Marsiske, M., Ball, K., Elias, J., Koepke, et al. (2006, December 20). Long-term effects of cognitive training on everyday functional outcomes in older adults. *Journal of the American Medical Association, 296,* 2806–2814.

Appendix

Alternative Growth Curve Models

A number of growth curve models were considered as alternatives to those described by Equation 1. Here we present these models and discuss their respective strengths and weaknesses.

One set of models considered assumes that rates of change are person-specific functions of the time since baseline evaluation and/or the number of occasions of measurement. The simplest of these models can be written as

$$Y[o]_n = i_n + \mathrm{Time}[o] \times s_n + u[o]_n, \qquad \text{(A1)}$$

where $Y[o]_n$ is the observed score of person n at occasion o, i_n is the growth curve intercept of person n, $\mathrm{Time}[o]$ is the time (in years) that has elapsed since the baseline assessment (i.e., 0, 0.23, 1.23, 2.23, 3.23, 5.23), s_n is the growth curve slope of person n, and $u[o]_n$ is the unexplained component for person n at occasion o. This model assumes only one source of variance in change and therefore confounds change that may be due to age-related maturation and change that may be due to the experience of repeated testing. Change is assumed to occur linearly, and therefore any potential nonlinear change in cognitive performance over time is not captured. Moreover, because performance is a function of time since baseline evaluation, rather than age at testing, the model fails to capitalize on age at testing as a source of information (for a discussion, see McArdle et al., 2002).

Assumptions about linear change in the above model can be relaxed by allowing the shape of the growth curve to be produced by the data. Such a growth curve can be written as

$$Y[o]_n = i_n + B[o] \times r_n + u[o]_n, \qquad \text{(A2)}$$

(*Appendixes continue*)

where r_n represents nonlinear change, scaled by occasion (i.e., $B[o]=0$, 1, B[1], B[2], B[3], B[5]). Again, only one source of variation in change is assumed, and age-related information is neglected.

An elaboration of the above two models is one that includes allowances for both linear and nonlinear sources of change. This model can be written as

$$Y[o]_n = i_n + \mathrm{Time}[o] \times s_n + B[o] \times r_n + u[o]_n. \quad \text{(A3)}$$

We again label the person-specific linear component, scaled by time since baseline evaluation, as s_n and the person-specific nonlinear component, scaled by occasion, as r_n. However, because age-related information is still neglected, and s_n and r_n are therefore on similar scales, it may not be justified to conceptualize these s_n and r_n components as individually representative of maturation and retest effects, respectively.

A second set of models considered assumes that rates of change are person-specific functions of age at testing and/or the number of occasions of measurement. A simple form of such a model can be written as

$$Y[o]_n = i_n + \mathrm{Age}[o]_n \times s_n + u[o]_n, \quad \text{(A4)}$$

where $\mathrm{Age}[o]_n$ corresponds to the age of the individual at any given occasion, centered at 65 years. As with the time-based linear model, this model does not account for nonlinear change. However, it is able to incorporate the age at testing as an additional source of information, under the assumption that age-related differences are informative about age-related changes (Bell, 1953).

Maturational components and retest components can be considerably separated by combining the models described by Equations A2 and A4 to one in which maturation is scaled according to the age of the individual but retest effects are scaled according to occasion of measurement (e.g., Ferrer et al., 2005; McArdle et al., 2002). This model can be written as

$$Y[o]_n = i_n + \mathrm{Age}[o]_n \times s_n + B[o] \times r_n + u[o]_n. \quad \text{(A5)}$$

This model is very similar to that described by Equation 1, with the difference being that the age basis is specific to the individual rather than the cohort (i.e., subscript *g* Equation 1 is replaced by *n*) and no cohort differences in the shape or magnitude of the retest effects are permitted.

Results

Tables A1 and A2 report fit statistics and parameter estimates for the above-described models fit to the reasoning and speed data, along with the conditional relations described by Equations 2–5. These outputs are also provided for the model described by Equation 1, with the shape and mean of the retest component, mean maturational component, mean intercept, conditional relations, and all residual variance terms constrained to be equal across groups.

A number of observations are of note. First, because the time- and occasion-basis models are nested within one another, as are the age- and occasion-basis models, we can directly compare their fits. In both cases, the models allowing for both linear and nonlinear sources of change fit the data best. Second, the Time + Occasion basis models produce curves (i.e., basis coefficients) that are difficult to interpret as distinctly representative of retest and maturation components, as the nonlinear components peak at the second assessment but subsequently decline (which is uncharacteristic of retest components, which are likely to accumulate with experience and decay more slowly with time) and the linear components have nonsignificant positive means (inconsistent with maturational decline). Alternatively, the Age + Occasion basis models produce more readily interpretable retest and maturation components, as the nonlinear components have positive means and approximately asymptotic shapes and the linear components have negative means. Finally, it is of particular note that for all models, the relations between hypothesized cognitive reserve variables and intercept and change components are very similar, overwhelmingly inconsistent with moderation hypotheses but consistent with stability hypotheses.

Table A1
Fit Indices and Parameter Estimates for Alternative Growth Curve Models of Reasoning

Parameter	Time and occasion basis (structural equation growth model)			Age and occasion basis (random effects growth model)			Age and occasion basis (multiple-group structural equation growth model): Linear + Latent basis (Equation 1)
	Linear basis by time (Equation A1)	Latent basis by occasion (Equation A2)	Linear + Latent basis[a] (Equation A3)	Linear basis by age (Equation A4)	Latent basis by occasion (Equation A2)	Linear + Latent basis[a] (Equation A5)	
Model fit indices							
χ^2	313.407	71.282	13.262		71.282		243.804
df	29	25	20		25		180
$-2 \times$ Log Likelihood	26464.93	26222.806	26164.786	23129.632	22893.840	22720.648	26051.956
Free parameters	13	17	22	13	17	22	30
CFI	.943	.991	1		.991		.987
TLI	.945	.990	1		.990		.990
RMSEA	.119	.052	0		.052		.051
AIC	26490.93	26256.806	26208.785	23155.631	22927.840	22764.648	26111.957
BIC	26549.907	26333.929	26308.592	23214.608	23004.964	22864.455	26248.057
Regression parameters							
i on educ (β_{ei})	0.719^*	0.722^*	0.748^*	0.714^*	0.722^*	0.566^*	0.639^*
i on vocab (β_{vi})	0.411^*	0.404^*	0.405^*	0.483^*	0.404^*	0.525^*	0.481^*
s on i (β_{is})	0.010		0.011	-0.015^*		-0.026^*	-0.025^*
s on educ (β_{es})	-0.036^*		−0.034	0.004		0.017	0.015
s on vocab (β_{vs})	−0.006		−0.006	0.001		0.003	0.004
r on educ (β_{er})		−0.126	−0.088		−0.126	−0.096	−0.111
r on vocab (β_{vr})		−0.027	−0.010		−0.027	0.017	0.013
r on i (β_{ir})		0.067^*	0.028		0.067^*	0.008	0.016
vocab on educ (β_{ev})	1.670^*	1.671^*	1.671^*	1.671^*	1.671^*	1.673^*	1.694^*
Basis coefficients							
Y[BL] on s	0^b	0^b	0^b	$age_{BL,n} - 65^b$	0^b	$age_{BL,n} - 65^b$	$age_{BL,g} - 65^b$
Y[PT] on s	0.23^b	0^b	0.2^b	$age_{BL,n} - 64.77^b$	0^b	$age_{BL,n} - 64.77^b$	$age_{BL,g} - 64.77^b$
Y[1] on s	1.23^b	0^b	1.23^b	$age_{BL,n} - 63.77^b$	0^b	$age_{BL,n} - 63.77^b$	$age_{BL,g} - 63.77^b$
Y[2] on s	2.23^b	0^b	2.23^b	$age_{BL,n} - 62.77^b$	0^b	$age_{BL,n} - 62.77^b$	$age_{BL,g} - 62.77^b$
Y[3] on s	3.23^b	0^b	3.23^b	$age_{BL,n} - 61.77^b$	0^b	$age_{BL,n} - 61.77^b$	$age_{BL,g} - 61.77^b$
Y[5] on s	5.23^b	0^b	5.23^b	$age_{BL,n} - 59.77^b$	0^b	$age_{BL,n} - 59.77^b$	$age_{BL,g} - 59.77^b$
Y[BL] on r	0^b	0^b	0^b	0^b	0^b	0^b	0^b
Y[PT] on r	0^b	1^b	1^b	0^b	1^b	1^b	1^b
YR1 on r	0^b	0.690^*	0.654^*	0^b	0.690^*	0.966^*	0.952^*
Y[2] on r	0^b	0.767^*	0.677^*	0^b	0.767^*	1.264^*	1.236^*
Y[3] on r	0^b	0.868^*	0.733^*	0^b	0.867^*	1.625^*	1.584^*
Y[5] on r	0^b	0.410^*	0.102	0^b	0.410^*	1.596^*	1.529^*
Residual variances							
reasoning residual variance (σ_y^2)	9.089^*	9.352^*	8.124^*	9.495^*	9.353^*	8.066^*	8.070^*
i residual variance (σ_i^2)	46.397^*	45.497^*	45.069^*	44.701^*	45.494^*	48.061^*	46.566^*
s residual variance (σ_s^2)	0.215^*		0.281^*	0.100^*		0.077^*	0.090^*
r residual variance (σ_r^2)		-3.456^*	−1.403		-3.458^*	0.986^*	0.912^*
vocab residual variance (σ_v^2)	73.302^*	73.311^*	73.300^*	73.289^*	73.312^*	73.294^*	73.075^*
Latent variable means							
Mean i (υ_i)	48.798^*	47.459^*	45.069^*	50.587^*	47.459^*	52.555^*	51.287^*
Mean s ($\upsilon_s + \beta_{is} \times \upsilon_i$)	0.073		0.125	-0.140^*		-0.561^*	-0.527^*
Mean r ($\upsilon_r + \beta_{ir} \times \upsilon_i$)		2.534^*	2.468^*		2.534^*	2.518^*	2.515^*

Note. All parameters are unstandardized. Because age at testing varied considerably across individuals, all age-and-occasion-basis random effects growth models were fit with the Random option of Mplus, which has a provision for individually varying times of observation. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; AIC = Akaike information criterion; BIC = Bayesian information criterion; i = latent growth curve intercept; s = maturational slope; r = retest component; educ = education; vocab = vocabulary; Y[BL] = baseline; Y[PT] = 12-week posttest; Y[1] = first annual; Y[2] = second annual; Y[3] = third annual; Y[5] = fifth annual; $age_{BL,n}$ = age at first testing; $age_{BL,g}$ = approximate group age at first testing.
[a] Denotes the best-fitting model by nested model comparisons relative to the two previous models. [b] Indicates that a parameter was fixed.
$^* p < .05$.

(*Appendixes continue*)

Table A2
Fit Indices and Parameter Estimates for Alternative Growth Curve Models of Speed

	Time and occasion basis (structural equation growth model)			Age and occasion basis (random effects growth model)			Age and occasion basis (multiple-group structural equation growth model): Linear + Latent basis
Parameter	Linear basis by time (Equation A1)	Latent basis by occasion (Equation A2)	Linear + Latent basis[a] (Equation A3)	Linear basis by age (Equation A4)	Latent basis by occasion (Equation A2)	Linear + Latent basis[a] (Equation A5)	(Equation 1)
Model fit indices							
χ^2	243.121	40.999*	18.44		40.999*		278.669*
Degrees of freedom	29	25	20		25		180
$-2 \times$ Log Likelihood	28884.044	28681.922	28659.362	25510.938	25352.956	25124.986	28449.068
Free parameters	13	17	22	13	17	22	30
CFI	.926	.994	1		.994		.96
TLI	.929	.994	1		.994		.969
RMSEA	.103	.030	0		.030		.063
AIC	28910	28715.9	28703.4	25536.9	25387	25168.99	28509.068
BIC	28969	28793	28803.2	25595.9	25464.1	25268.79	28645.168
Regression parameters							
i on educ (β_{ei})	0.494*	0.528*	0.509*	0.276	0.528*	0.214	0.257
i on vocab (β_{vi})	0.194*	0.166*	0.169*	0.267*	0.166*	0.309*	0.269*
s on i (β_{is})	0.013		0.014	−0.013		−0.021*	−0.019*
s on educ (β_{es})	0.010		0.016	0.020		0.009	0.01
s on vocab (β_{vs})	−0.005		−0.004	−0.002		−0.005	−0.004
r on educ (β_{er})		−0.142	−0.129		−0.142	0.002	−0.043
r on vocab (β_{vr})		−0.009	0.002		−0.009	0.012	0.015
r on i (β_{ir})		0.228*	0.170*		0.228*	0.062	0.070*
vocab on educ (β_{ev})	1.675*	1.675*	1.675*	1.675*	1.675*	1.676*	1.698*
Basis coefficients							
Y[BL] on s	0[b]	0[b]	0[b]	$age_{BL,n}$ −65[b]	0[b]	$age_{BL,n}$ −65[b]	$age_{BL,g}$ −65[b]
Y[PT] on s	0.23[b]	0[b]	0.2[b]	$age_{BL,n}$ −64.77[b]	0[b]	$age_{BL,n}$ −64.77[b]	$age_{BL,g}$ −64.77[b]
Y[1] on s	1.23[b]	0[b]	1.23[b]	$age_{BL,n}$ −63.77[b]	0[b]	$age_{BL,n}$ −63.77[b]	$age_{BL,g}$ −63.77[b]
Y[2] on s	2.23[b]	0[b]	2.23[b]	$age_{BL,n}$ −62.77[b]	0[b]	$age_{BL,n}$ −62.77[b]	$age_{BL,g}$ −62.77[b]
Y[3] on s	3.23[b]	0[b]	3.23[b]	$age_{BL,n}$ −61.77[b]	0[b]	$age_{BL,n}$ −61.77[b]	$age_{BL,g}$ −61.77[b]
Y[5] on s	5.23[b]	0[b]	5.23[b]	$age_{BL,n}$ −59.77[b]	0[b]	$age_{BL,n}$ −59.77[b]	$age_{BL,g}$ −59.77[b]
Y[BL] on r	0[b]	0[b]	0[b]	0[b]	0[b]	0[b]	0[b]
Y[PT] on r	0[b]	1[b]	1[b]	0[b]	1[b]	1[b]	1[b]
Y[1] on r	0[b]	0.944*	0.915*	0[b]	0.944*	1.218*	1.216*
Y[2] on r	0[b]	0.959*	0.897*	0[b]	0.959*	1.487*	1.482*
Y[3] on r	0[b]	0.940*	0.853*	0[b]	0.940*	1.776*	1.763*
Y[5] on r	0[b]	0.561*	0.358	0[b]	0.561*	1.800*	1.786*
Residual variances							
speed residual variance (σ^2_y)	24.795*	25.047*	23.228*	26.215*	25.051*	22.890*	22.959*
i residual variance (σ^2_i)	68.978*	56.735	57.609*	62.403	56.729	61.798*	59.613*
s residual variance (σ^2_s)	0.333*		0.421*	0.093		0.017	−0.004
r residual variance (σ^2_r)		−8.147*	−5.013		−8.160*	2.261*	2.360*
vocab residual variance (σ^2_v)	73.285*	73.288*	73.286*		73.288*	73.280*	73.065*
Latent variable means							
mean i (υ_i)	47.739*	45.810*	45.825*	51.703*	45.810*	53.006*	51.291*
mean s ($\upsilon_s + \beta_{is} \times \upsilon_i$)	0.140*		0.077	−0.346*		−0.802*	−0.776*
mean r ($\upsilon_r + \beta_{ir} \times \upsilon_i$)		3.214*	3.196*		3.214*	3.216*	3.185*

Note. All parameters are unstandardized. Because age at testing varied considerably across individuals, all age-and-occasion-basis random effects growth models were fit with the Random option of Mplus, which has a provision for individually varying times of observation. CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root-mean-square error of approximation; AIC = Akaike information criterion; BIC = Bayesian information criterion; i = latent growth curve intercept; s = maturational slope; r = retest component; educ = education; vocab = vocabulary; Y[BL] = baseline; Y[PT] = 12-week posttest; Y[1] = first annual; Y[2] = second annual; Y[3] = third annual; Y[5] = fifth annual; $age_{BL,n}$ = age at first testing; $age_{BL,g}$ = approximate group age at first testing.
[a] Denotes the best-fitting model by nested model comparisons relative to the two previous models. [b] Indicates that a parameter was fixed.
* $p < .05$.

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