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Global and Domain-Specific Changes in Cognition Throughout Adulthood

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Normative adult age-related decrements are well documented for many diverse forms of effortful cognitive processing. However, it is currently unclear whether each of these decrements reflects a distinct and independent developmental phenomenon, or, in part, a more global phenomenon. A number of studies have recently been published that show moderate to large magnitudes of positive relations among individual differences in rates of changes in different cognitive variables during adulthood. This suggests that a small number of common dimensions or even a single common dimension may underlie substantial proportions of individual differences in aging-related cognitive declines. This possibility was directly examined using data from 1,281 adults 18–95 years of age who were followed longitudinally over up to 7 years on 12 different measures of effortful processing. Multivariate growth curve models were applied to examine the dimensionality of individual differences in longitudinal changes. Results supported a hierarchical structure of aging-related changes, with an average of 39% of individual differences in change in a given variable attributable to global (domain-general) developmental processes, 33% attributable to domain-specific developmental processes (abstract reasoning, spatial visualization, episodic memory, and processing speed), and 28% attributable to test-specific developmental processes. Although it is often assumed that systematic and pervasive sources of cognitive decline only emerge in later adulthood, domain-general influences on change were apparent for younger (18–49 years), middle aged (50–69 years), and older (70–95 years) adults.

Keywords: cognitive aging, longitudinal change, dedifferentiation, common cause hypothesis

Average levels of performance on many different forms of effortful cognitive processing decline continuously with adult age. Beginning as early as the third decade of life, average levels of performance on measures of reasoning, spatial visualization, episodic memory, and processing speed begin to decline (Salthouse, 2009). Two major, as of yet unanswered questions within the field of cognitive aging concern the extent to which the mechanisms that underlie these declines occur at global versus specific levels and the extent to which this pattern differs at different ages. In other words, it is currently unclear (a) whether each of the deficits that have been observed on different cognitive tasks represents an independent developmental phenomenon in need of a unique mechanistic account or a more general developmental phenomenon operating across tasks and (b) if general influences on cognitive aging do exist, whether these influences are present in early adulthood, when the deficits first occur, or emerge in later adulthood when the deficits become more severe. These issues were directly addressed for the current project by analyzing the dimensionality of individual differences in aging-related cognitive changes in adults ranging in age from 18 to 95 years. I directly addressed these issues in the current project by analyzing the dimensionality of individual differences in aging-related cognitive changes in adults ranging in age from 18 to 95 years.

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Background

One reason to expect that changes in many different cognitive variables may fall along a small number of dimensions is that parsimonious few-factor representations of the cross-sectional interrelations among cognitive variables are well established (Carroll, 1993; Salthouse, 2004; cf. Tucker-Drob, 2009; Tucker-Drob & Salthouse, 2008). Approximately 40% of the between-person variation in performance on diverse batteries of cognitive tests can be accounted for by a single dimension, often termed *g*, along which people can be ordered relative to one another (see, Deary, 2001, for a general overview). Upward of an additional 25% of this variation can be accounted for by secondary dimensions, sometimes termed *broad abilities, cognitive abilities*, or *cognitive domains*. Many different sources of evidence support this balanced domain-general and domain-specific account. The most basic evidence comes from the general pattern of correlations that has been replicated across many different cognitive test batteries and samples of participants. The pattern is one in which tests hypothesized to rely on the same cognitive domain are highly related and tests hypothesized to measure different cognitive domains are more moderately related (see, e.g., Deary, 2001, for a general overview). A related line of evidence is that, using a factor analytic model, the tests' relations with one another can be very closely approximated by way of their mutual relations to a combination of domain-specific factors and a domain-general factor (Carroll, 1993). Evidence for the discriminant validity of the cognitive domains is further derived from their relations to exogenous variables. For example, measures associated with different domains exhibit different lifespan age gradients (Li et al., 2004; McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002; Salthouse, 2004); exhibit different patterns of relations to demographic variables such as education (Salthouse, 2004), gender (Salthouse & Ferrer-Caja, 2003), and job performance (Gottfredson, 2003); are associated with partially independent genetic and environmental influences (Petrill, 1997); and are associated with different neuroanatomical substrates (Colom et al., 2009).

Past Cross-Sectional and Longitudinal Approaches

Age-heterogeneous cross-sectional data have often been examined with the hope of gaining insight into the dimensionality underlying aging-related deficits. Using multivariate cross-sectional data, Salthouse and colleagues (Salthouse, 2004, 2009; Salthouse & Ferrer-Caja, 2003) have demonstrated that aging-related influences on many different cognitive variables can be well accounted for by way of aging-related influences on a small number of dimensions: typically a high in magnitude negative influence of age on the general factor and moderate in magnitude negative influences of age on an episodic memory dimension and a processing speed dimension.

Cross-sectional examinations of individual and age-related differences, however, do not provide direct insight about the factor structure of individual difference in longitudinal changes. For example, it is possible that common age-related influences on multiple variables are produced by similar age-related differences in mean performance even when variables do not change in unison for specific individuals (Hofer & Sliwinski, 2001). In fact, that multivariate longitudinal data are needed to draw conclusions about the dimensionality of individual differences in changes is nearly a truism. Multivariate longitudinal cognitive test data, along with improved analytical (Bryk & Raudenbush, 1987; McArdle & Epstein, 1987) and computational methods for analyzing them, are becoming increasingly available. A number of recent studies (Anstey et al., 2003; Ferrer, Salthouse, McArdle, Stewart, & Schwartz, 2005; Sliwinski, Hofer, & Hall, 2003; Lemke & Zimprich, 2005; Reynolds, Gatz, & Pederson, 2002; Sliwinski & Buschke, 2004; Tucker-Drob, Johnson, & Jones, 2009; Zelinski & Stewart, 1998; Zimprich & Martin, 2002) have reported correlations among longitudinal changes in multiple cognitive variables. Consistent with hypotheses that common sources of aging-related cognitive changes operate across multiple domains of functioning, the majority of these studies have found the correlations to be positive, medium to large in magnitude, and significantly different from zero. Plainly put, a person who declines quickly in one cognitive domain relative to his or her peers is also likely to be declining quickly relative to his or her peers in another cognitive domain.

Four studies (Hertzog, Dixon, Hultsch, & MacDonald, 2003; Lindenberger & Ghisletta, 2009; Reynolds, Gatz, & Pederson, 2002; Wilson et al., 2002) have, in fact, reported that a single common factor accounts for large proportions (i.e., between approximately 30% and 60%) of individual differences in age-related changes in cognitive abilities. However, each of these studies has either only included one or two measures reflective of the same cognitive domain or only correlated changes in composite scores or latent constructs rather than individual variables. This level of analysis reduces the ability to make inferences about whether a more complex factor structure of changes might hold—in other words, whether domain-specific dimensions of change exist in addition to a domain-general dimension. By investigating the organizational structure of changes at the level of multiple individual tests, I was able to evaluate this possibility.

Different Patterns at Different Stages of Adulthood?

A second major issue concerns whether the covariational structure of cognitive changes differs at different ages. Early adulthood cognitive declines are often dismissed as uncommon and unsystematic (see Salthouse, 2009, for a review and rebuttal). It is perhaps because of this perspective that the majority of cognitive aging researchers focus their attention and resources on middle and late adulthood, when general and systematic sources of decline are presumed to arise (de Frias, Lövdén, Lindenberger, & Nilsson, 2007). The implication of contentions that general and systematic declines only emerge in middle and late adulthood is that in young adulthood, changes across multiple cognitive domains should vary minimally and be uncorrelated or modestly correlated, whereas in middle and later adulthood, correlated changes in different cognitive domains should emerge and strengthen.

Objectives

The current project addresses two main questions. First, to what extent do aging-related cognitive declines represent a single global phenomenon, a few domain-specific phenomena, or many variable-specific phenomena? Second, if global patterns of aging-related cognitive declines exist, do they only emerge in later adulthood? I address the first question by examining the factor structure of individual differences in aging-related changes in performance on 12 cognitive variables representative of four domains of effortful cognitive processing. If any of the causal mechanisms of adult cognitive declines operate across multiple domains (i.e., if cognitive aging is, in part, a global phenomenon), at least one common factor should account for changes in multiple cognitive variables. Here, a number of alternative factor models of changes are considered, including a single common factor model, a spatial/figural and verbal/numeric two-factor model, a hierarchical four-factor model, and a model derived from exploratory analyses. The second question is addressed by estimating factor structures of cognitive changes for younger, middle-aged, and older adult age groups. For this project, the younger group is composed of adults 49 years of age and younger, an age range much younger than is typically examined in longitudinal studies of cognitive aging. If general sources of aging-related deficits only emerge in middle or late adulthood, as some would argue, a common change factor should only be supported in these latter two age groups (50 to 69 years and 70 to 97 years, respectively).

This project is innovative in two major respects. First, it comprehensively examines the dimensionality underlying individual differences in cognitive changes in adulthood. Although some previous research suggests that changes in different cognitive variables are indeed positively interrelated, no researcher has yet conducted a systematic examination of alternative dimensional representations of such patterns. Second, this project examines whether global sources of individual differences in cognitive changes occur before middle adulthood. Most previous investigations have only included middle-aged and older adults and have therefore been limited in their capabilities to examine age differences in patterns of change interrelations.

Method

Participants

The data analyzed here were collected as part of the Virginia Cognitive Aging Project, which is an ongoing longitudinal study being conducted at the Cognitive Aging Lab at the University of Virginia. Collection of baseline data as part of independent cross-sectional studies began in 2001 and is ongoing. Participants are recruited from the Charlottesville, Virginia, community with newspaper advertisements, flyers, and referrals from other participants. To be eligible for participation, individuals must speak English and have completed at least a high school education. Ages span continuously from 18 to 95 years of age. Beginning in 2004, participants returned to the Cognitive Aging Lab for a second round of testing on many of the same cognitive tests that they were originally administered. Only a subset of participants were invited to return for retesting during a given year to create variability in the longitudinal retest intervals across persons. This variability in retest intervals helps to attenuate the confounding (in traditional longitudinal studies, complete confounding) between the amount of time that participants have matured and the amount of previous experience that participants have had with being tested. The growth curve models used capitalize on this feature to separate total change into components associated with developmental change and components associated with retest-related learning.

A total of 2,853 participants were initially tested between 2001 and 2006 and therefore were eligible for retesting. Of those, 559 had moved, 970 could not be contacted, 80 were not interested in participating again, four had developed dementia and were living in assisted care facilities, and nine had died. The remaining 1,227 participants (94% of those who could be contacted and had not moved, died, or developed dementia) returned for retesting. Attrition/retention information is not available for the 444 participants tested in 2007 because only a fraction of them were contacted for retesting in 2008. Of those participants initially tested in 2007 who were contacted, 54 returned in 2008, resulting in total longitudinal sample of 1,281. The distributions of participants by age group and longitudinal interval are reported in Table 1. It can be seen that the majority of longitudinal participants were tested 2 or 3 years apart, with some participants tested as close as a year apart and small proportions tested as much as 6 and 7 years apart.

Measures

Participants were administered a battery of up to 12 cognitive tests (three for each cognitive domain) selected to measure abstract reasoning, spatial visualization, episodic memory, and processing speed.

Abstract reasoning refers to the ability to reason in novel ways, make use of unfamiliar information, identify relations, draw inferences, and form concepts. It was measured using the Matrix Reasoning test (Raven, 1962), the Shipley Abstraction test (Zachary, 1986), and the Letter Sets test (Ekstrom, French, Harman, & Derman, 1976).

Spatial visualization refers to the ability to mentally rotate, manipulate, and reason with two- and three-dimensional patterns. It was measured using the Spatial Relations test (Bennett, Seashore, & Wesman, 1997), the Paper Folding test (Ekstrom et al., 1976), and the Form Boards test (Ekstrom et al., 1976).

Episodic memory refers to the ability to retrieve and explicitly state previously encoded information. It was measured using the Logical Memory test (Wechsler, 1997b), the Free Recall test (Wechsler, 1997b), and the Paired Associates test (Salthouse, Hancock, Meinz, & Hambrick, 1996).

Processing speed refers to the ability to quickly and efficiently carry out mental operations. It was measured using the Digit Symbol substitution test (Wechsler, 1997a), the Letter Comparison test (Salthouse & Babcock, 1991), and the Pattern Comparison test (Salthouse & Babcock, 1991).

The paired associates test and all tests of abstract reasoning and spatial visualization were scored using a two-parameter logistic item response theory (IRT) model. The Free Recall test, Logical Memory test, and all three tests of processing speed could not be scored with IRT because the Free Recall and Logical Memory tests required sequential responses that are not independent of one another (e.g., multiple trials of recalling the same list of words or recalling multiple idea units from each story), and the processing speed tests did not contain distinct categorical items. For these tests, scores were therefore standardized to the z metric on the basis of the test means and standard deviations of all available data

Table 1
Cross-Sectional and Longitudinal Sample Sizes by Age Group and Time Lag

Age range at baseline	Age at baseline in years		Longitudinal interval							
	M	*SD*	1-year *n*	2-year *n*	3-year *n*	4-year *n*	5-year *n*	6-year *n*	7-year *n*	*N* of all time lags
18–49	35.42	9.90	67	190	114	57	19	6	2	455
50–69	58.55	6.01	96	231	146	58	22	9	0	562
70–95	77.30	5.06	44	123	70	13	11	2	1	264
Total sample	54.20	17.30	207 (16.2%)	544 (42.5%)	330 (25.8%)	128 (10.0%)	52 (4.1%)	17 (1.3%)	3 (0.2%)	1,281

from the Virginia Cognitive Aging Project. Because the distributions were approximately normal for all scores, no other transformations were performed. Means and standard deviations of baseline performance on the 12 cognitive tests are presented in Table 2. A comparison of returning and nonreturning participants is provided in the next section.

Descriptive Analyses

Basic characteristics of the participants are presented in Table 2. One way of evaluating the selectivity of a sample involves comparing scores on a number of standardized measures with the scores for the normative sample of the Wechsler Adult Intelligence Scale (3rd ed.; Wechsler, 1997a) and Wechsler Memory Scale (3rd ed.; Wechsler, 1997b), which was matched to the U.S. population on a number of demographic variables including gender, ethnicity, years of education, and region of residence. Age-adjusted scaled scores have means of 10 and standard deviations of 3 in the normative sample, but the scaled score means in the current sample were all above 11 (with standard deviations very close to 3). Although this indicates that the individuals in this sample were functioning above the average of the normative sample, this was true to nearly the same extent at all ages, as the correlations between age and the scaled scores were very low. Results from this data set may therefore be most applicable to people with higher than average levels of functioning, but the age comparisons should be meaningful because there is little evidence that participants of different ages were differentially representative of their age groups and because the amounts of variability were similar to those observed in the normative sample.

Longitudinal participants, compared with those who did not return, were very similar in the proportion of participants that were female (65% for returners compared with 66% for nonreturners); self-rated health (mean rating for returners = 2.20 out of 5, on a scale of 1 = *excellent* to 5 = *very poor*, compared with 2.18 out of 5 for nonreturners); years of education (mean years completed for returners = 15.7 compared with 15.6 for nonreturners); and scaled scores on the Wechsler Adult Intelligence Scale Digit Symbol test (11.5 for returners compared with 11.4 for nonreturners), the Wechsler Memory Scale Logical Memory test (12.1 for returners, compared with 11.8 for nonreturners), and the Wechsler Memory Scale Free Recall test (12.6 for returners compared with 12.3 for nonreturners). Returning participants were approximately six years older, on average, than nonreturning participants (mean age for returners = 54.2 years compared with 47.3 years for nonreturners), which is largely attributable to the fact that a number of younger participants were university students who were very likely to move away after graduating.

Table 2
Descriptive Statistics by Age Group (Baseline Assessment)

	Age group						Full longitudinal sample (N = 1,281)			
	18–49 years (n = 455)		50–69 years (n = 562)		70–95 years (n = 264)					
Variable	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	Age *r*	r_{OE}
Age in years	35.42	9.90	58.55	6.01	77.30	5.06	54.20	17.30		
Digit Symbol scaled score	11.09	2.90	11.71	2.73	11.97	2.71	11.54	2.81	.13	
Logical Memory scaled score	11.40	2.76	12.40	2.77	12.61	2.80	12.09	2.82	.18	
Recall scaled score	11.95	3.35	13.23	3.06	12.29	3.01	12.58	3.27	.08	
Education	14.98	2.35	16.23	2.55	16.0	3.04	15.74	2.65	.21	
Male (0) vs. female (1)	.68		.67		.58		.65		−.04	
MMSE	28.62	1.70	28.83	1.50	28.09	1.99	28.61	1.71	−.11	
Abstract reasoning measures										
Matrix Reasoning (θ)	.32	.88	−.04	.74	−.70	.70	−.05	.87	−.48	.81
Shipley Abstraction (θ)	.26	.92	−.01	.79	−.55	.88	−.02	.91	−.34	.87
Letter Sets (θ)	.13	.83	.06	.78	−.49	.80	−.03	.84	−.25	.79
Spatial visualization measures										
Spatial Relations (θ)	.17	1.01	.02	.85	−.50	.67	−.03	.91	−.29	.89
Paper Folding (θ)	.24	.87	.03	.78	−.47	.70	−.00	.84	−.33	.75
Form Boards (θ)	.22	.92	−.11	.80	−.58	.72	−.10	.88	−.39	.88
Episodic memory measures										
Recall (*z*)	.34	.84	.17	.81	−.64	.92	.07	.92	−.38	.92
Paired Associates (θ)	.28	.88	.08	.87	−.48	.73	.04	.89	−.32	.85
Logical Memory (*z*)	.15	.99	.10	.88	−.33	.99	.03	.96	−.17	.86
Processing speed measures										
Digit Symbol (*z*)	.47	.84	−.02	.76	−.87	.76	−.02	.93	−.54	
Pattern Comparison (*z*)	.50	.93	.01	.81	−.75	.77	.03	.96	−.51	.87
Letter Comparison (*z*)	.46	.88	−.01	.86	−.71	.84	.01	.96	−.45	.82

Note. r_{OE} = odd–even split half reliability estimate corrected with the Spearman–Brown prophecy formula; θ = scores were produced from a two-parameter logistic item response theory model; MMSE = Mini-Mental State Examination; *z* = scores were computed by subtracting the mean and dividing by the standard deviation of all available data from the Virginia Cognitive Aging Project. Reliabilities for the Digit Symbol test could not be computed because it does not contain distinct items.

Results

Univariate Growth Curve Models

The analyses for the current project made use of a growth curve modeling approach with provisions for retest effects (McArdle & Woodcock, 1997).[1] This model specifies performance at a given measurement occasion to be determined by three factors: (a) an initial *level* factor, which represents performance at baseline; (b) a developmental change factor, or growth curve *slope*, which represents yearly change in performance over the longitudinal study period; and (c) a *retest effect* factor, which represents the benefits from having been previously tested. Equations formally representing the growth models implemented are provided in Appendix A and Appendix B. Growth curve models were estimated with full information maximum likelihood in Mplus (Muthén, & Muthén, 1998–2010).

In initial growth models, each variable's retest effect was allowed to have a mean and a variance; however, the retest variance estimates were frequently very close to zero or even negative. Removing this random effect on the retest component allowed for modeling of the interactions between age and retest and between baseline performance and retest. Such interactions would not have been identifiable simultaneously with the random retest effect using the two-occasion data that were available. The selected specification therefore included a random effect on baseline performance, a random effect on developmental change, an Age × Baseline Performance interaction, an Age × Developmental Change interaction, a baseline performance–developmental change covariance, a constant retest component, an Age × Retest interaction, and a Baseline Performance × Retest interaction.

The benefit of previous testing experience differed for the different tests, ranging from approximately 6% to 35% of the magnitude of the level standard deviations, which is similar in magnitude to estimates based on other methods and types of data (e.g., Hausknecht, Halpert, Di Paolo, & Gerrard, 2007; Salthouse & Tucker-Drob, 2008). Retest-corrected estimates of mean yearly developmental change also differed for the different tests, with magnitudes ranging from approximately 2% to 10% of the standard deviations of the levels. The lower estimate suggests that the average performance level is displaced by a full standard deviation after 50 years of aging, whereas the upper estimate suggests that this displacement occurs after only 10 years of aging. The between-person standard deviation of this effect ranged from approximately 6% to 19% of the magnitude of the level standard deviations, which is small relative to standard deviations of the levels but fairly large compared with the estimated magnitudes of mean yearly longitudinal changes.

Confirmatory Factor Models of Change

The 12 univariate growth curve models, which had previously been specified individually, were combined into all-encompassing multivariate growth curve models, with separate factor models superimposed on the levels and the changes. After McArdle (1998), these are termed *factors of curves* models (see Appendix A for formal specification). The factor structure of the levels was prespecified on the basis of previous research on the factor structure of cognitive variables in general (Carroll, 1993) and these variables more specifically (e.g., Salthouse, 2004). Standardized parameter estimates for this prespecified factor structure of the levels are presented in Table 3. Note that the standardized loading of abstract reasoning on the general factor is slightly out of bounds (i.e., greater than 1). This is not much of a concern, because the parameter is very close to being in bounds.

Four plausible alternative factor models of the changes (i.e., the growth curve slopes) were focused on for this project. These were a *single common change* factor model (Model A); a *spatial/figural change* and *verbal/numeric change* two-factor model (Model B); and an *abstract reasoning change*, *spatial visualization change*, *episodic memory change*, and *processing speed change* four-factor model both with and without a higher order factor (Models C and D, respectively). Standardized parameter estimates for these alternative factor structures of the slopes are presented in Table 4.

The single common change factor model (Model A) provides initial evidence for domain-general sources of variation in adult cognitive changes, as all standardized loadings are positive and statistically significant. This model is perhaps the simplest representation of change interrelations. Multifactor models can potentially provide more nuanced representations of change interrelations.

The two-factor model (Model B) again provide evidence of domain-general sources of variation in cognitive changes, as the loadings are positive and the two factors correlate very highly, at .87. This high factor intercorrelation suggests that a model with spatial/visual and verbal/numeric change factors may not have adequate levels of discriminant validity.

The four-factor models (Models C and D) provide clear evidence for both domain-general and domain-specific dimensions of individual differences. The high positive loadings of the changes in the individual variables on the first-order factors are strong evidence for the convergent validity of domain-specific changes, and the moderate-sized first-order factor interrelations (and, in the hierarchical version of this model, moderately high loadings of the first-order factors the higher order general factor) are consistent with a partially global basis of the changes across domains. It is interesting that this solution indicates that change in abstract reasoning loads at unity on the higher order global change factor. This parallels cross-sectional findings that fluid intelligence and general intelligence are statistically isomorphic (Gustafsson, 1988; Tucker-Drob & Salthouse, 2009).

Fit indices for the above-described one-, two-, and four-factor models are presented in the top portion of Table 5. It can be seen that the best fitting of the factor models of change was the one containing the four correlated change factors. Even according to the fit statistics that correct for degrees of freedom and penalize for lack of parsimony, the four correlated change factors model fit the data best. The support for this four-factor structure suggests that changes may indeed be occurring along the same dimensions as those underlying individual differences in performance on a given occasion. Moreover, that all of the loadings and correlations are positive in all models suggests that changes in performance that

[1] All tables indicate whether unstandardized parameter estimates were different from zero at $p < .01$ or $p < .05$. Following convention, both the $p < .01$ and $p < .05$ levels are interpreted as statistically significant. Standardized parameter estimates are reported in the tables for ease of interpretation.

Table 3
Standardized Parameter Estimates for Factor Structure of Initial Levels of Cognitive Performance

	Level structure				
Variable	Abstract reasoning	Spatial visualization	Episodic memory	Processing speed	General factor
Matrix Reasoning	.78				
Shipley Abstraction	.82				
Letter Sets	.85				
Spatial Relations		.89			
Paper Folding		.88			
Form Boards		.70			
Recall			.78		
Paired Associates			.77		
Logical Memory			.82		
Digit Symbol				.69	
Pattern Comparison				.64	
Letter Comparison				.70	
Abstract Reasoning	—				1.06
Spatial Visualization	.87	—			.83
Episodic Memory	.67	.53	—		.65
Processing Speed	.61	.43	.48	—	.58

Note. All parameters are significant at $p < .01$.

occur on many different cognitive tests during adulthood can, in part, be characterized as a global, domain-general phenomenon.

Exploratory Factor Models of Change

After the above-reported confirmatory models were fit, an exploratory factor analysis was performed. This exploratory analysis was carried out in a multistage process. First, a 12 $\times$ 12 correlation matrix, corrected for measurement error using split-half reliability estimates, was produced for the simple longitudinal change scores. This correlation matrix, which overwhelmingly consisted of positive values, was then submitted to an exploratory factor analysis with oblique rotation. On the basis of the eigenvalue greater than 1 criterion, four factors were retained, all of which were positively correlated with one another. The exploratory solution approximated simple structure, in that the tendency was for each change score to have a high loading on a single factor and low loadings on the remaining factors. On the basis of these results, a four-factor confirmatory model was then superimposed directly onto the multivariate growth curve models, with each slope only loading on the factor on which the corresponding change score loaded the highest in the exploratory solution. Parameter estimates for this model are presented in the right portion of Table 4, and its fit indices are presented in Table 5 (Model E). It can be seen that the configural factor structure from this exploratory model was quite similar to that from the purely confirmatory model that had been fashioned on the basis of the well-established cross-sectional structure. Although the fit indices indicate that this exploratory model describes the data better than the purely confirmatory model does, the two models are substantively very similar, and both fit quite well in absolute terms. Finally, the factor intercorrelations for both solutions are similar to one another. Because of these similarities and because it did not capitalize on potentially chance patterns of relations, the four-factor confirmatory model was accepted as the optimal representation of the structural pattern of cognitive changes in adulthood.

Moving From Factors of Changes to Changes in Factors

That the factor structure of changes that closely resembles the factor structure of levels fit the data well suggests that developmental changes might actually occur at the factor level. This hypothesis was explicitly considered by fitting growth models to factors representing abstract reasoning, spatial visualization, episodic memory, and processing speed, each of which had its own measurement model that was assumed to be measurement invariant over time. Moreover, each of the 12 individual tests was specified to include a constant retest component, a Baseline Factor Score $\times$ Retest interaction, and an Age $\times$ Retest interaction (as in McArdle et al., 2002). After McArdle (1988), this is termed a *curves of factors* model (see Appendix B for formal specification).

Correlations among the levels and slopes of the resulting curves of factors models are reported in Table 6. In the rightmost columns are the loadings from a model in which the levels and slopes are specified to load on respective common factors. These results are consistent with those from the factors of curves models reported earlier. As in the confirmatory four-factor solution presented in Table 4, the correlations among the changes in each domain are moderate to large in magnitude, as are the loadings of these changes on a common factor. Moreover, the higher order factor solutions for levels and slopes are very similar.

The fits of the curves of factors models are reported in the bottom portion of Table 5 (Models F and G). The curves of factors and the factors of curves models are not nested within one another, but because they are based on the same data, their absolute fits can be compared. Because fewer change components are estimated by the curves of factors model, it is more parsimonious than factors of curves model, but its fit is poorer as a consequence. Inspection of the Akaike information criterion and Bayesian information crite-

Table 4
Standardized Parameter Estimates for Alternative Factor Structures of Longitudinal Slopes

	Single factor (A)	Spatial/figural and verbal/numeric (B)		Confirmatory four-factor solution (C and D)					EFA-informed CFA of growth curve slopes (E)			
Variable	F1	F1 (Spatial/figural)	F2 (Verbal/numeric)	F1	F2	F3	F4	Higher order general factor	F1	F2	F3	F4
Matrix Reasoning slope	.69**	.76**		.77**						.92**		
Shipley Abstraction slope	1.01**		1.03**	.96**					1.01**			
Letter Sets slope	.80**		.79**	.81**					.78**			
Spatial Relations slope	.58**	.56**			.98**					.78**		
Paper Folding slope	.48**	.34			.90**					.64**		
Form Boards slope	.54**	.41**			.49**						.50**	
Recall slope	.99**		.99**			1.16**					1.01**	
Paired Associates slope	.66**		.70**			.80**					.82**	
Logical Memory slope	.76*		.82**			.92**					.88**	
Digit Symbol slope	—		—				—				—	
Pattern Comparison slope	.40**	.42**					.58**					.38**
Letter Comparison slope	.67**		.68**				.97**					1.37**
F1		—		—				1.09**	—			
F2		.87**	—	.76**	—			.72**	.98**	—		
F3				.55**	.41**	—		.54**	.75**	.50**	—	
F4				.52**	.24†	.31**	—	.52**	.45**	.26**	.28**	—

Note. The dashes in the Digit Symbol row indicate that standardized loadings for Digit Symbol could not be computed because although its unstandardized loading was significantly positive in all models considered, its model-implied slope variance was very close to zero. EFA = exploratory factor analysis; CFA = confirmatory factor analysis.
* $p < .05$. ** $p < .01$.

Table 5
Fit Indices for Alternative Multivariate Growth Curve Models

Model	Log likelihood	Free parameters	RMSEA	CFI	TLI	AIC	BIC
A. Single common change factor	−98,513.521	161	.029	.931	.932	197,349.043	198,179.062
B. Spatial/visual and verbal/numeric factors	−98,478.469	171	.029	.933	.934	197,298.938	198,180.510
C. Four correlated change factors	−98,468.799	172	.028	.934	.935	197,281.599	198,168.327
D. Four change factors with higher order factors	−98,483.197	169	.029	.933	.934	197,304.393	198,175.655
E. EFA-informed CFA model	−98,456.532	172	.028	.935	.936	197,257.063	198,143.791
F. Correlated curves of four factors	−99,319.930	108	.041	.861	.868	198,855.859	199,412.642
G. Factors of curves of four factors	−99,336.948	105	.041	.860	.868	198,883.896	199,425.212

Note. RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker–Lewis index; AIC = Akaike information criterion; BIC = Bayesian information criterion; EFA = exploratory factor analysis; CFA = confirmatory factor analysis.

rion indices suggest that this difference is appreciable. Moreover, although the comparative fit index and Tucker–Lewis index statistics are in the acceptable range for the factors of curves model, they are on the low end for the curves of factors model. The root-mean-square error of approximation estimates for all solutions are very good. All in all, the curves of factors model does not fit as well as the factors of curves model, but both models fit the data acceptably and both produce substantively congruent results in that they both indicate that approximately half of the individual differences in change occurring in a given cognitive domain is shared across domains.[2]

Comparisons of Age Groups

The results to this point have been consistent with the hypothesis that individual differences in rates of change across different cognitive domains are positively interrelated and that these positive change interrelations at the first-order level can be described by loadings on a common factor at the second-order level. The next set of analyses asks whether the positive relations among rates of change in different cognitive domains exist in both early adulthood and late adulthood. Two questions are addressed: (a) Can positive change interrelations be detected at all phases of adulthood? If so, (b) is domain-general variation in cognitive changes more pronounced for older adults than for younger adults?

Multiple group models were fit, with group membership assigned according to age at baseline testing occasion. Individuals 18 to 49 years of age were assigned to the youngest age group, individuals 50 to 69 years of age were assigned to the middle age group, and individuals 70 to 95 years of age were assigned to the oldest age group. These groupings were chosen so that the younger group would be composed of an age range younger than is typically examined in longitudinal studies of cognitive aging and so that the older group would be composed of individuals past the typical age of retirement.[3] To reduce the complexity associated with fitting multiple-group growth curves to 12 variables simultaneously, multiple-group analyses were based on composite scores representative of abstract reasoning, spatial visualization, episodic memory, and processing speed. Growth curves were each specified to have a random initial level, a random slope, a level–slope covariance, a constant retest effect, and a Level × Retest Effect interaction.

Parameter estimates from each age group are presented in Table 7. Two features are particularly relevant. First, for all three groups, there is evidence for moderate positive intercorrelations among rates of change across domains. This same pattern is demonstrated by the moderately large positive loadings of the slopes on a common factor. Second, there is some indication that there is greater variation in the slopes in the oldest age group. To formally compare age differences in the amount of common variation in changes across the four domains, I imposed cross-age group equality constraints on the unstandardized loadings of the slopes on the common change factor. These constraints did not result in a significant reduction in model fit, $\chi^2(8) = 9.50$, $p = .31$. The hypothesis of higher common variance at older ages therefore cannot be statistically supported by this analysis. These results indicate that there are global sources of aging-related changes of comparable magnitudes at all ages.

Robustness of Results

Although the substantial majority, if not all, of the participants included in the current study were cognitively healthy adults, one may wonder whether failures to exclude preclinical cases of dementia may have contributed to the positive change interrelations reported here. This does not appear to have been the case, as the same general patterns of statistically significant positive relations among estimated rates of developmental changes persisted across age groups when (a) participants scoring below 27 on the Mini-Mental State Examination (a common dementia screening instrument; Folstein, Folstein, & McHugh, 1975) at any occasion were excluded; (b) participants with age-adjusted scores greater than 2.5 standard deviations from the mean on one or more composite measure of abstract reasoning, spatial visualization, episodic memory, or processing speed at any occasion were excluded; and (c) participants whose change score on any of the four composite measures was more than 2.5 standard deviations from the mean change score for that measure were excluded.

Discussion

Although "common cause" models of cognitive aging have been popular for some time (Baltes & Lindenberger, 1997; Salthouse,

[2] Duncan, Duncan, and Strycker (2006) in fact recommend comparing the substantive conclusions drawn from the factors of curves and curves of factors models rather than directly comparing their fits.

[3] Indeed, de Frias et al. (2007, p. 389) have suggested that correlations among rates of change in different cognitive domains only arise after 65 years of age, which is what they referred to as "old age" (p. 389).

Table 6
Standardized Parameter Estimates for Structural Portion of Curves of Factors Models

Variable	Standard deviation of change	Correlations: Abstract reasoning	Correlations: Spatial visualization	Correlations: Episodic memory	Correlations: Processing speed	Higher order structure: General factor	Higher order structure: Global change factor
Levels							
Abstract reasoning		—				.96**	
Spatial visualization		.72**	—			.76**	
Episodic memory		.56**	.44**	—		.59**	
Processing speed		.45**	.31**	.36**	—	.47**	
Slopes							
Abstract reasoning	.09**	—					1.00**
Spatial visualization	.08**	.74**	—				.67**
Episodic memory	.12*	.72**	.58**	—			.70**
Processing speed	.08*	.78**	.39*	.65**	—		.77**

Note. In this table, each standard deviation of change has been scaled relative to the standard deviation of the respective level (i.e., by taking ratio of the standard deviation of the change to the standard deviation of the level).
* $p < .05$. ** $p < .01$.

1994, 2004), only recently has it become well acknowledged that multivariate longitudinal data are needed to begin to rigorously test many of their predictions. Deater-Deckard and Mayr (2005) recently lamented the dearth of multivariate longitudinal research and commented that the "ultimate answer to the question of whether cognitive aging is a general factor or a multifaceted phenomenon will come from careful longitudinal data that allow for testing whether changes in one ability explain changes in other abilities" (p. 25). They further commented that "it will be critical [to uncover] the dimensionality of change across a wide range of cognitive abilities" (p. 25). The current project took an approach consistent with these recommendations. The major finding is illustrated in Figure 1, which presents the hierarchical factor solution of individual differences in rates of longitudinal changes. Above the solution is a pie diagram displaying the average proportions of variation associated with global change, domain-specific change, and test-specific change dimensions. As the title of this article indicates, these findings suggest that the process of cognitive aging is characterized by both global and domain-specific declines. Theories and accounts of cognitive aging that only focus on global changes and those that only focus on domain-specific changes are therefore both likely to be incomplete.

Table 7
Standardized Parameter Estimates From Multiple Group Models of Cognitive Changes in Younger Adults (18–49 Years), Middle Aged Adults (50–69), and Older Adults (70–95 Years)

Age and measure	Standard deviation of change	Correlations: Abstract reasoning slope	Correlations: Spatial visualization slope	Correlations: Episodic memory slope	Correlations: Processing speed slope	Standardized loading on global change factor
18–49 years						
Abstract reasoning slope	.08*	—				.72**
Spatial visualization slope	.09**	.23	—			.36†
Episodic memory slope	.11*	.61**	.47**	—		.73**
Processing speed slope	.15**	.44*	.10	.46*	—	.62**
50–69 years						
Abstract reasoning slope	.11**	—				.84**
Spatial visualization slope	.10**	.69**	—			.78**
Episodic memory slope	.13**	.53**	.38*	—		.58**
Processing speed slope	.09	.52*	.58**	.53*	—	.73**
70–95 years						
Abstract reasoning slope	.11**	—				.85**
Spatial visualization slope	.08*	.38	—			.62*
Episodic memory slope	.27**	.40*	.54**	—		.52**
Processing speed slope	.14*	.83**	.47	.32*	—	.86**

Note. In this table, each standard deviation of change has been scaled relative to the standard deviation of the respective level (i.e., by taking ratio of the standard deviation of the change to the standard deviation of the level). To keep all groups' standard deviations on comparable metrics, the standard deviation in the denominator is always from the young group.
† $p = .05$. * $p < .05$. ** $p < .01$.

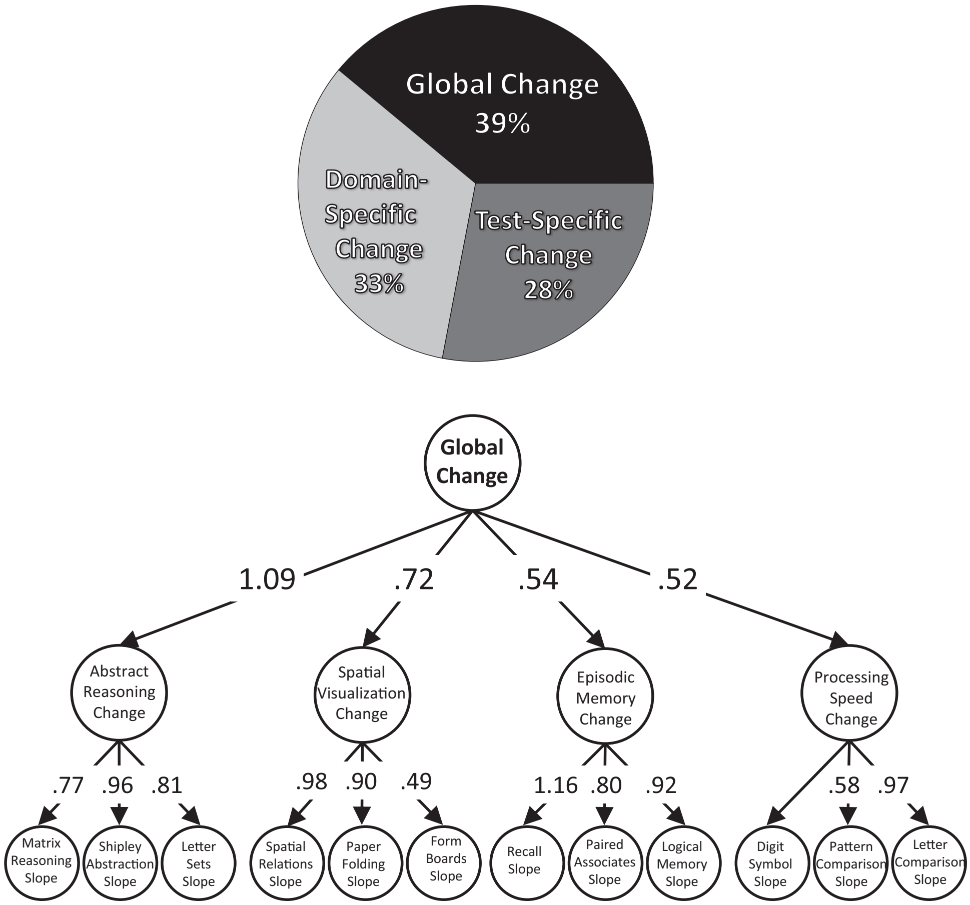

Figure 1. Graphical representation of the standardized factor solution for longitudinal slopes. Note that the standardized loadings for Digit Symbol slope could not be computed because, although its unstandardized loading on processing speed change was significantly positive, its model-implied variance was very close to zero.

A second major finding reported here is that a common change dimension was apparent in the youngest group of participants (ages 18 to 49 years). That the magnitude of variation in cognitive changes accounted for by this dimension was not statistically different from those found in the older age groups runs counter to predictions by those such as de Frias et al. (2007), who recently predicted that "how individuals change in one cognitive ability is increasingly related to the ways they change in other cognitive abilities with advancing age" (p. 381). Rather, it appears that the global and pervasive sources of cognitive change that are apparent in later life in fact emerge at similar ages as mean declines emerge, that is, in early adulthood.

Limitations, Assumptions, and Future Directions

Two-occasion data. Two-occasion data strongly limit the sorts of models that can be fit. Because the retest intervals varied in this project, change was able to be decomposed into development and retest components. However, these complex models stretch the available information to its limit (for discussions, see McArdle & Woodcock, 1997; McArdle et al., 2002). As the Virginia Cognitive Aging Project continues, added occasions of observation, combined with the variable retest interval design, will provide a great deal of added modeling flexibility. For example, with multiple time points, one can begin to consider models that capture the shapes of individual trajectories in detail and perhaps even accurately diagnose individual change points.

Limited time lags. A related limitation of the current study was that the longitudinal time lag was limited to a maximum of 7 years, and the majority of participants had intervals of less than 4 years. The most apparent implication of the limited time lags is reduced power to detect changes that occur very slowly, that is, over many years. However, formal power analyses (e.g., Hertzog, Lindenberger, Ghisletta, & von Oertzen, 2006) suggest that the low power of shorter time lags can be compensated for with more reliable measures, more frequent measurements, or larger sample sizes. The brevity of time lags therefore seems to have its most major consequences when researchers are interested in accurately capturing the shape of a slow nonlinear process, tracking event occurrences that are few and far between, diagnosing change points, or comparing different phases of development.

Convergence. The unavailability of long-term longitudinal data forces researchers to seek out surrogate sources of developmental information. The most extreme type of surrogate approach is the pure cross-sectional study, in which different people of different ages are compared to make inferences about how individuals change over development. In the current study, longitudinal information was used to make inferences about patterns of change, but an age-comparative approach was still used to make inferences about how these change patterns differ across younger, middle, and older adults. The assumption that age-related differences and age-related changes can be combined to examine the same developmental phenomenon has sometimes been termed the *convergence assumption* (Bell, 1953). To avoid making this assumption, a researcher interested in comparing the patterns of change that occur surrounding 30 years and surrounding 80 years of age, for example, would have to obtain at least 50 years of longitudinal data, which is, in most cases, not feasible.

Causal inference. This project was concerned with characterizing the behavioral aspects of normative aging. Specifically, estimated changes in performance on multiple cognitive tasks were used to make inferences regarding whether and how cognition changes both qualitatively and quantitatively with adult age. Given that all behaviors must have some neurobiological basis, the current findings are informative about how neurobiological influences associated with aging are manifest. However, on the basis of behavioral data alone, it would be entirely speculative to make inferences about what those neurobiological influences are. A corollary of this rationale is that examining the factor structure of cognitive changes can help us to identify the number of behavioral dimensions (within the set of variables examined) on which the causes of changes operate but cannot actually tell us about how many distinct causes there are at the biological level. A global dimension of cognitive decline could, for instance, be the outcome of multiple independent biological mechanisms, each broadly affecting cognition.

Dimensionality of decline or dimensionality of maintenance? It is also likely that individual differences in aging-related behavioral changes reflect both individual differences in the causes of cognitive deficits and individual differences in the resistance to cognitive deficits. The current finding that large proportions of individual differences in cognitive changes operate along a single dimension could suggest that the causes of cognitive decline have global effects on functioning or, more optimistically, that the inhibitors of cognitive decline have globally protective effects. Future research concerned with identifying correlates of cognitive changes would help to enable the separation of these two sources.

Why people differ from one another in rates of change versus why people change. Finally, it is of note that although these results are quite informative about individual differences in changes, they offer somewhat less new information about mean changes. That is, longitudinal data provide unique and powerful information about the patterns by which some people decline faster than others, but they provide very similar information to cross-sectional data about the patterns by which people decline on the whole. Although a tenable assumption may be that the reasons that some people decline faster than others are the same as the reasons that people are declining on average, it is also viable to conceptualize these reasons as independent of one another. An example of one such possibility was offered above: It may be the case that the causes of large mean declines are biological but the causes of individual differences in such rates are protective/lifestyle in nature. Cross-sectional analyses such as those by Salthouse (2004) and Salthouse and Ferrer-Caja (2003) may be best suited for making inferences about mean age-related cognitive changes, whereas longitudinal analyses may be best suited for making inferences about individual differences in age-related cognitive changes.

Breadth of outcomes. The current investigation was concerned with characterizing the dimensionality of changes in a selection of cognitive variables that decline continuously with adult age. A diverse battery of tests requiring effortful processing was therefore examined. Tests of previously acquired knowledge were not examined, as performance on such tests tends to improve through most of adulthood, presumably as a result of the accumulation of experience. Also not examined here were measures of health, physiology, or sensation and perception (e.g., vision and hearing). Some researchers (e.g., Baltes & Lindenberger, 1997; Lindenberger & Ghisletta, 2009) have emphasized a perspective that a single dimension of decline underlies knowledge, health, and sensory domains, in addition to multiple cognitive domains, particularly in old age. It will therefore be important for future work to examine how aging-related changes in all of these different domains relate to one another.

Predictors of change. With the general features of aging-related longitudinal cognitive changes becoming better established, researchers can more systematically examine variables that have been hypothesized to predict such changes and whether such predictive relations operate at domain-general or domain-specific levels. Variables that are frequently mentioned as being related to late-life cognitive functioning include mental activity, physical exercise, social engagement, and educational attainment (see Hertzog, Kramer, Wilson, & Lindenberger, 2008, for a review). Future research will benefit from systematically examining how measures of these hypothesized protective factors relate to the global and domain-specific facets of aging-related changes.

Conclusion

In summary, multivariate growth curve models were applied to two-occasion, 12-variable data from 1,281 adults ranging in age from 18–95 years, with up to seven years between assessments. Results were generally supportive of a positive manifold of change interrelations. A series of alternative factor models were fit to these change interrelations. Results were consistent with a hierarchical factor structure of changes in performance very similar to that previously established for levels of performance. An average of 39% of individual differences in change in a given variable was attributable to global developmental processes, 33% was attributable to domain-specific developmental processes, and 28% was attributable to variable-specific developmental processes. Age-comparative analyses produced evidence that a global change factor accounts for comparable magnitudes of change variation in 18–49 year, 50–69 year, and 70–95 year age groups. These results together suggest that the process of cognitive aging is both a domain-general and a domain-specific phenomenon and that domain-general sources of change begin early in the aging process. Crucial next steps will be to identify the biological and environmental predictors and correlates of cognitive changes and determine where on this hierarchical structure their influences operate.

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Appendix A

Formula for the Factors of Curves Model

The *factors of curves model* combines lower order growth curve models with higher order factor models. The growth curves are written as

$$Y[t]_{w,x,z,n} = y_{0,w,x,n} + A[t]_{w,z} \cdot y_{s,w,z,n} + B[t]_{w} \cdot y_{r,w,n} + e[t]_{w,n}, \quad \text{(A1)}$$

where $Y[t]_n$ is score of person n on variable Y at time t, $y_{0,n}$ is the unobserved baseline performance score (initial level) for person n, $y_{s,n}$ is the unobserved change score (slope) of person n, $y_{r,n}$ is a second unobserved change score for person n, and $e[t]_n$ is a unique factor score (disturbance) of person n at time t. By setting $A[t]$ to be a function of time since baseline, $y_{s,n}$ is interpreted as person-specific developmental change. Similarly, by setting the coefficient $B[t]$ to be equal to the number of prior assessments, $y_{r,n}$ can be interpreted as the person-specific retest effect. The subscript w denotes the cognitive test, the subscript x denotes the factor ($G_{0,x}$) on which the level (y_0) loads, and the subscript z denotes the factor ($G_{s,z}$) on which the slope (y_s) loads. These factor models are written as

$$y_{0,w,x,n} = \upsilon_{0,w,x} + \lambda_{0,w,x} \cdot G_{0,x,n} + u_{0,w,n}, \quad \text{(A2)}$$

$$y_{s,w,z,n} = \upsilon_{s,w,z} + \lambda_{s,w,z} \cdot G_{s,z,n} + u_{s,w,n}, \quad \text{(A3)}$$

where the υs represent regression intercepts, the λs represent factor loadings, and the *u*s represent residuals.

Appendix B

Formula for the Curves of Factors Model

The *curves of factors model* combines lower order factor models with higher order growth curve models. The lower order factor models are written as

$$Y[t]_{w,x,n} = \upsilon_{w,x} + \lambda_{w,x} \cdot G[t]_{x,n} + B[t]_{w,n} \cdot y_{r,w,n} + e[t]_{w,x,n}, \quad \text{(B1)}$$

where $Y[t]_n$ is score of person n on variable Y at time t, υ is a regression intercept, λ is a factor loading, $G[t]_{x,n}$ is the score of person n on factor x at time t, y_r is a variable-specific retest effect, and e is a variable-specific unique factor score. The growth curve portions of the models are written as

$$G[t]_{x,n} = y_{0,x,n} + A[t]_{x,n} \cdot y_{s,x,n} + u[t]_{x,n,} \quad \text{(B2)}$$

where $y_{0,n}$ is the unobserved baseline performance score (initial level) for person n and $y_{s,n}$ is the unobserved change score (slope) of person n.

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