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Exploring structural dynamics within and between sensory and intellectual functioning in old and very old age: Longitudinal evidence from the Berlin Aging Study ☆

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Abstract

Cross-sectional and longitudinal analyses of age-heterogeneous samples have revealed correlational links between and within intellectual, sensory, and sensorimotor domains. Due to basic limitations of cross-sectional designs and a reluctance to disentangle antecedent–consequent relations in longitudinal designs, the functional significance and dynamics of these links have remained unclear. Advanced structural equation models allow representing multivariate longitudinal changes as a function of time-based and directed relations. We applied this methodology to longitudinal data from the Berlin Aging Study (at inception total $N = 516$; age range = 70–103 years) to explore the structural dynamics among perceptual speed, verbal knowledge, close visual acuity, and distance visual acuity. We found reliable, occasion-based, age-partialed latent regression paths that influence longitudinal changes within and across intellectual and sensory domains. We conclude that intellectual and sensory domains are dynamically linked in old and very old age, and discuss implications of this finding for theories of cognitive aging.

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1. Introduction

Recent years have seen a revival of Galton's proposal of a causal link between sensory functioning and intelligence (e.g., Galton, 1883). For instance, Deary (1994), in a review of relations between sensory discrimination, defended Galton's sense–intelligence hypothesis by arguing that its early dismissals were due to a selective emphasis on disconfirming results. In line with earlier proposals by Spearman (1904) and Burt (1909–1910), Deary argued that the presence of moderate but consistent correlations between sensory performance and intellectual abilities are in need of theoretical explanation (cf. Li, Jordanova, & Lindenberger, 1998).

In recent years, this increase in interest in sensory and other non-intellectual correlates of intellectual functioning has been particularly pronounced in cognitive aging research (e.g., Li & Lindenberger, 2002). Much attention has been paid to a wide range of sensory and sensorimotor functional indicators, sometimes referred to as indicators of "primary aging," "biomarkers," or measures of functional, biological, and physiological age (Anstey, Lord, & Smith, 1996; Anstey, Stankov, & Lord, 1993; Birren & Cunningham, 1985; Busse, 1969). Among the investigated markers of sensory and sensorimotor functioning are measures of visual and auditory acuity, forced expiratory volume, grip strength, lower limb strength, vibration sense, body sway and gait, balance, simple visual and auditory reaction time, tactile information processing, olfaction, and more (Acton & Schroeder, 2001; Anstey, 1999b; Anstey, Lord, & Williams, 1997; Anstey et al., 1996, 1993; Baltes & Lindenberger, 1997; Bennett & Eklund, 1983; Clement, 1974; Horn, 1982a; Horn & Stankov, 1982; Li et al., 1998; Lindenberger and Baltes, 1994; Rabbitt, 1991; Roberts, Stankov, Pallier, & Dolph, 1997; Salthouse, Hambrick, & McGuthry, 1998; Salthouse, Hancock, Meinz, & Hambrick, 1996; Schaie, 1996; Stankov, 1986; Stankov & Anstey, 1997).

Evidence of interrelations between intellectual and sensory-sensorimotor functioning has accumulated over recent years. At times, the available evidence seemed so convincing that some biomarkers were proposed to be functionally related to more or less specific intellectual abilities, within old age, in general, or both. Examples include: (a) the inclusion of sensory and motor abilities as lower-order intellectual abilities within the general hierarchical theory of intelligence of Gf/Gc by Cattell (1971) and Horn (1982b) (e.g., Horn & Stankov, 1982; Stankov, 1986; Stankov & Anstey, 1997; Stankov & Horn, 1980); (b) the mediating role of some biomarkers between chronological age and intellectual performance (e.g., Anstey, 1999a; Anstey & Smith, 1999; Stankov & Anstey, 1997); (c) the use of sensory and sensorimotor functions as indicators of domain-general senescent changes in brain physiology (e.g. Anstey, Luszcz, & Sanchez, 2001; Baltes & Lindenberger, 1997; Lindenberger & Baltes, 1994, 1997); and (d) the fundamental, initiating functional role of biomarkers within the cascade hypothesis (e.g., Birren, 1964; Birren & Cunningham, 1985).

Generally, developmental theories are based on assumptions about antecedent–consequent relations in intraindividual change and interindividual differences therein (e.g., Baltes, 1968; Nesselroade, 1970; Schaie, 1962). The different theoretical propositions about ontogenetic links between intellectual, sensory, and sensorimotor domains of functioning attempt to structure these antecedent–consequent relations (cf. Baltes & Nesselroade, 1979). At the same time, most existing evidence about the interrelations among intellectual, sensory, and sensorimotor domains of functioning is based on cross-sectional data. Given the strong and generally untested assumptions needed to generalize from between-subjects age differences to within-subjects age changes (e.g., Lindenberger & Pötter, 1998; Hofer & Sliwinski, 2001), many have stressed the urgent need for longitudinal comparisons, especially when investigating theories about interdomain links that unfold over time (Anstey, 1999a; Baltes, Reese, & Nesselroade, 1977; Baltes & Lindenberger, 1997; Lindenberger & Baltes, 1994; Lindenberger, Scherer, & Baltes, 2001; Molenaar, Huizenga, & Nesselroade, 2003; Sliwinski and Hofer, 1999).

Recently, due to the increasing availability of repeated-measures data, researchers have begun to explore longitudinal associations among variables representing sensory, sensorimotor, and intellectual domains of functioning (e.g., Anstey, Hofer, & Luszcz, 2003; Hofer, Berg, & Era, 2003; Li, Aggen, Nesselroade, & Baltes, 2001; Li & Lindenberger, 2002). In terms of statistical methods, several authors used latent growth models (LGMs, McArdle, 1986) to define relations among levels and changes. This approach is, under certain conditions, analogous to multilevel, hierarchical linear, and random effects models (cf. Ghisletta & Lindenberger, 2004; Lindenberger & Ghisletta, 2004; Raudenbush, 2000). Advantages common to all LGMs, which make them attractive for evaluation of developmental theories, are that they allow (a) removing unrelated variance (e.g., measurement error); (b) defining the two mathematically independent but statistically potentially related concepts of "level" and "change;" (c) defining various functional forms of change (i.e., LGMs are not limited to linear patterns, though in practice linearity is the most widely applied specification); (d) defining change over different time dimensions (e.g., chronological age, occasions of measurement, time to a clinical diagnosis, time to death), and (e) evaluating predictions about covariances and means/intercepts simultaneously.

Recent applications of LGMs have promoted our understanding of functional associations among old-age changes in intellectual, sensory, and sensorimotor domains. Anstey et al. (2003) applied LGMs to vision, hearing, memory, perceptual speed, and verbal performance indicators, assessed three times in the Australian Longitudinal Study of Ageing. Because the authors included several indicators for each domain, they defined a factor for each domain to then super-impose a LGM to model level and change in each domain (cf. curves of factors; McArdle, 1988). Change was defined over occasions of measurement. Different specifications of LGMs allowed testing for reliable average change effects as well as for interindividual differences around the average change (i.e., fixed and random effects, respectively, in longitudinal multilevel modeling terminology). Anstey and colleagues found: (a) reliable average change and reliable variance in change for memory, perceptual speed, vision, and hearing, but not for verbal performance; (b) when not controlling for important covariates, significant correlations among all level components and possible change components; (c) when controlling for age, sex, education, depression, and health, smaller but still significant correlations between all level components and all, except for memory and hearing, change components. Thus, intellectual and sensory changes were well captured by a combination of domain-general and domain-specific factors. The common factor may point to the existence of domain-general mechanisms. Conversely, the specific factors point to mechanisms whose timing, pace, or neuronal substrate is specific to a given domain.

One drawback of standard applications of the LGM is that it underscores *static* aspects of any change process while neglecting its *dynamic* aspects. By static aspects we mean that the analyses define relations among the states of the system (i.e., the actual variables' values). By dynamic aspects, on the other hand, we mean that the variables' changes, rather than their values, become the main focus of the analyses. The static representation has been criticized because it does not fully capture the developmental information inherent in longitudinal data (e.g., Boker, 2002; Molenaar, 1985; McArdle, 1982; Nesselroade, 2000; Nesselroade & Schmidt McCollam, 2000; Newell & Molenaar, 1998). In the standard LGM a person's level and change scores are posited constant across time. The two scores are added in a time-dependent manner such that the final predicted score also reflects longitudinal change. Hence, LGMs, and most classical change models, describe, in a more or less sophisticated way, change.

However, developmental sciences should not be limited to descriptions of change. They should aim at understanding more intimately the structure of change, the substantive meaning of change, and, ultimately, what causes change (Baltes & Nesselroade, 1979). To move towards these goals, a number of dynamical systems techniques, linear and nonlinear, have been proposed. One such system is the Dual Change Score Model (DCSM) introduced by McArdle and Hamagami (2001) and McArdle (2001).

2. Present objectives

The goals of the present paper are to explore: (a) longitudinal changes among select marker variables of intellectual and sensory functioning in very old age; (b) static links among their changes; and finally (c) dynamic links among their changes. We analyze the longitudinal sample of the Berlin Aging Study (BASE, $N=516$ at inception; Baltes & Mayer, 1999; Baltes, Mayer, Helmchen, & Steinhagen-Thiessen, 1993). All available data up to the fourth measurement occasion are analyzed, including data from participants measured on fewer than four occasions. We apply multivariate LGMs and the recently developed DCSM. Analyses were limited to four composite variables: (a) perceptual speed; (b) verbal knowledge; (c) close visual acuity; and (d) distance visual acuity.

With respect to intellectual functioning, the longitudinal assessment in BASE also includes verbal fluency and semantic memory. The restriction to perceptual speed and verbal knowledge was motivated by two main reasons. First, the multivariate DCSM is a rather advanced structural equation model that is not as easily specified, identified, and computed as the standard multivariate LGM. We hence preferred to limit the analyses to fewer variables to avoid calculation problems (e.g., empirical underidentification) and to obtain reliable findings. Second, and more importantly, it is well established that not all intellectual abilities relate equally strongly to sensory and sensorimotor functioning. In particular, intellectual abilities that can be categorized as markers of decline in fluid/mechanic abilities (Baltes, 1987; Cattell, 1971; Horn & Cattell, 1966) typically show relations of higher magnitude to variables from sensory and sensorimotor domains than intellectual abilities categorized as crystallized/pragmatic (e.g., Anstey et al., 1993; Baltes & Lindenberger, 1997; Lindenberger & Baltes, 1997; Singer, Verhaeghen, Ghisletta, Lindenberger, & Baltes, 2003). In earlier cross-sectional and longitudinal analyses of the BASE data set it was shown that perceptual speed and verbal knowledge are located at the two extremes of the fluid-crystallized spectrum as represented in the BASE cognitive battery (Lindenberger & Baltes, 1997; Singer et al., 2003). Therefore, the selection of intellectual abilities with documented divergent associations to biological and cultural systems of influence was intended to reveal differential relations to the two markers of sensory aging included in the present analysis. Specifically, and in accordance with Horn (1989) (cf. Table 5, p. 56), we rely on perceptual speed to indicate negative age differences in general speediness or Gs, which with advancing age becomes increasingly related to broad fluid abilities (or mechanics; e.g., Baltes & Lindenberger, 1997), and verbal ability to mark broad crystallized abilities (or pragmatics).

Vision is among the more frequently investigated sensory functions. Its correlational link to intellectual abilities in old age has been replicated in many studies and under various operationalization schemes (e.g., Anstey, 1999b; Anstey, Dain, Andrews, & Drobny, 2002; Lindenberger & Baltes, 1997; Salthouse et al., 1996; Schaie, 1996). Generally, correlational studies focus on visual acuity, rather than field vision, color vision, or visual contrast sensitivity (e.g., Anstey et al., 1993, 1997; Owsley & Sloane, 1990, but cf. Anstey et al., 2002, 2003). More often than not, close visual acuity is not distinguished from distance visual acuity, so that the general construct of visual acuity may represent either close or distance visual acuity, or a combination of the two.

However, available evidence suggests that close and distance visual acuity may differ in ways that are relevant to the purpose of this study (Lindenberger & Baltes, 1994; Marsiske et al., 1999). In work by Lindenberger and Baltes (1994), for example, interrelationships among chronological age, close and distance visual acuity, auditory acuity, and a psychometric battery of cognitive tasks were investigated in a preliminary sample of the BASE ($N=156$, mean age = 85 years, age range = 70–103 years). Vision was defined as a complex factor representing the distance visual acuity measurements assessed binocularly and a lower-order factor of close visual acuity assessed separately for the right and left eyes. In the model, the latter factor had a unique predictive relation to the perceptual speed factor; this finding held also after the exclusion from analyses of mildly and severely demented participants. The authors argued that not accounting for this specific effect might artificially augment the importance of vision on intellectual performance, primarily due to methodological reasons. In addition, declines in presbyopia, which affects close vision acuity, are quite common with advancing age, where declines in myopia, closely related to distance visual acuity, are not (Agarwal, 1947; Berens, 1947). Thus, for the purpose of this study, it seemed justified to represent distance and close visual acuity as separate factors.

Based on the foregoing considerations, the dynamic analysis of longitudinal relations within and across intellectual and sensory domains were guided by two broad expectations. First, we expected static interrelations among changes in intellectual and sensory markers. More precisely, we expected that the latent level and change scores of perceptual speed, verbal knowledge, close visual acuity, and distance visual acuity would correlate, as analyzed with a LGM, when their variance is reliable. Correlations among the level components resemble previously reported correlations among intellectual and sensory scores in the initial cross-sectional portion of BASE (Baltes & Lindenberger, 1997; Lindenberger & Baltes, 1994). To avoid the possibility that such interrelations exclusively reflect cross-sectional mean age trends, we also controlled for chronological age. Second, we predicted the presence of dynamic links within and between intellectual and sensory domains of functioning. Specifically, we expected some of the dynamic parameters within and between perceptual speed, verbal knowledge, distance visual acuity, and close visual acuity to be significant. Methodologically, this result would imply that standard LGM analyses provide a less comprehensive and theoretically informative statistical representation of within and between domain changes in intellectual and sensory functioning than DCSMs. When specifying the DCSMs, we also controlled for chronological age so that dynamic parameters were uncontaminated by cross-sectional mean age trends. In line with lifespan theories of cognitive development (Baltes, Lindenberger, & Staudinger, in press; Lindenberger, 2001), we expected that static (concurrent) and dynamic (occasion-based) intersystemic links to vision would be more pronounced for perceptual speed than for verbal knowledge. Empirically, perceptual speed has been repeatedly shown to be a strong marker of intellectual, and more generally behavioral, aging (Birren, 1974; Hertzog, 1989; Salthouse, 1983, 1996; Verhaeghen & Salthouse, 1997). The exploration of the precise nature of these links, such as the directionality of vision–perceptual speed relations, was implemented by a series of hypothesis tests operationalized as nested statistical comparisons (exploratory hypothesis testing via nested model comparisons; cf. Jöreskog & Sörbom, 1993). Compared to other theoretical perspectives (Anstey, 1999b; Birren, 1964), these tests were not guided by a priori assumptions about the direction of influence between dynamic aspects of sensory and fluid–mechanic changes.

3. Method

3.1. Participants

The BASE is an ongoing aging study of interdisciplinary nature, involving the fields of psychology, sociology and social policy, psychiatry, and internal medicine and geriatric medicine (Baltes & Mayer, 1999; Baltes et al., 1993). Five hundred and sixteen participants composed the initial longitudinal sample in 1989. The sampling strategy involved stratification by gender and by chronological age (70–74, 75–79, 80–84, 85–89, 90–94, 95 years and older), with 43 participants in each gender-by-age group (for further description and initial sample selectivity, see Lindenberger et al., 1999). During the first, third, and fourth wave of measurement, most variables were assessed, while on the second and, most recently, fifth wave, a subset of variables were measured. The analyses that follow are based on the first four occasions of measurement. Longitudinally, the total sample size decreased from 516 participants to 361 in the second, 244 in the third, and 164 in the fourth wave. Adjacent waves were separated in time from each other by about two years.

3.2. Intellectual abilities

Perceptual speed was assessed with the Digit Letter and the Identical Pictures tests, and verbal knowledge with the Vocabulary and the Spot-a-Word tests (for a detailed description see Lindenberger, Mayr, & Kliegl, 1993). Previous analyses (Lövdén, Ghisletta, & Lindenberger, 2004) revealed that possible retest effects were present only in the Identical Pictures test. Thus, we did not control for retest effects in the present analyses. Except for the Digit Letter test, the cognitive tests were administered with Macintosh SE30 computers equipped with touch-sensitive screens.

The Digit Letter test was timed with a limit of three minutes, and resembles the well-known Digit Symbol Substitution test of the WAIS (Wechsler, 1955). While a constant template with nine digit–letter pairings was shown, a maximum of 21 series of six digits each were consecutively shown. Participants were to pair each digit with the correct letter by pronouncing the letter as quickly as possible, according to the template. Upon completion of each series, a new series was shown to the participant. Two trials were administered, and the scores analyzed here represent the average across the two trials of the total number of pairings. The reliability of this test is high (Cronbach $\alpha = 0.96$; see Lindenberger & Reischies, 1999). The Identical Pictures test consisted of a maximum of 32 series of six figures, one of which was a target figure, five of which were response alternatives. Of the five response alternatives, only one matched the target figure. Participants were to touch the target among the response figures. Again two trials were administered and their total numbers of correct pairings within 80 s were averaged and analyzed here. The reliability of this test is fairly high (Cronbach $\alpha = 0.90$). The two tests correlated 0.79, 0.73, and 0.78 at wave 1, 3, 4, respectively (all p's < 0.01). The Vocabulary test was not timed and consisted of 20 words selected from the Vocabulary subtest of the German WAIS (HAWIE; Wechsler, 1982). The scores analyzed here are the sum of two independent raters' coding of participants' definitions of the words (possible codes were wrong, partially correct, and correct). The reliability of this test is fairly high (Cronbach $\alpha = 0.82$ and inter-coder reliability $= 0.96$). The Spot-a-Word test was again not timed and consisted of twenty series of one word and four pronounceable non-words. Participants were asked to select the word by touching it. Analyzed scores refer to the total number of correctly identified words. The reliability of this test is also fairly high (Cronbach $\alpha = 0.92$). The two tests correlated 0.65, 0.62, and 0.51 at wave 1, 3, 4, respectively (all p's < 0.01).

3.3. Sensory functions

Visual acuity was assessed with standard optometric procedures (Geigy, 1977), with and without corrective aids (e.g., glasses or contact lenses). A standard Snellen reading chart was presented at about 25 cm of distance from the participants' eyes, and a different standard Snellen reading chart was presented at a starting distance of 2.5 m. Close visual acuity (25 cm) was assessed for both eyes separately, while distance visual acuity (2.5 m) was measured binocularly. If individuals were not able to read any of the numbers or letters at a distance of 2.5 m, the distance was reduced. The distance visual acuity score was computed relative to the actual testing distance, following standard procedures.

For close vision, the scores analyzed here consist of the best measurement of right/left eye, with/without correction. For distance vision, the scores considered are the best assessment of with/without correction. We chose to consider the best values, which almost always coincided with the use of glasses, to be consistent with previous work on the wave 1 cross-sectional data (Lindenberger & Baltes, 1994; Marsiske et al., 1999) and because corrective devices should filter out, to a certain degree, peripheral variance (e.g., variance due to individual differences in the refractory properties of the lenses), thereby allowing for a more direct assessment of the portion of sensory loss that is central-neuronal in nature (cf. Lindenberger & Baltes, 1994). Reliability estimates for the vision measures are not provided because reliability calculations with only one or two items are problematic (e.g., Nunnally & Bernstein, 1994).

3.4. Transformations and descriptive statistics

The unit-weighted linear composites of perceptual speed (Digit Letter and Identical Picture), verbal knowledge (Vocabulary and Spot-a-Word), close visual acuity (best value of right/left eye, with/without optical correction) and distance visual acuity (best value of with/without optical correction) were re-expressed to have analogous scaling properties at time one only. Specifically, the four composite scores had a mean of 50 and a standard deviation of 10 in the parent sample at time one. This affine transformation greatly eases the interpretation of the results while it neither alters the psychometric properties of the scores nor does it eliminate longitudinal changes in means and variances.

The visual acuity assessments were collected during all four waves of measurement, while the intellectual ability tests were not administered during the second wave. However, we specify the LGMs and DCSMs to adjust for this data unbalance. Hence, all available data (e.g., including the wave-two visual acuity data) are retained in the analyses.

Table 1 presents the summary group statistics of the four composites considered at each measurement occasion. Besides presenting indices of mean, standard deviation, skewness, and kurtosis, we also present the N's in each cell of the table, to show the resulting unbalance in sample sizes. Low skewness and kurtosis indices justified the use of the statistical analyses presented next.

3.5. Statistical models

In addition to concurrent variable relations, the kind of hypotheses we intend to explore focus on time-lagged effects. That is, we are especially interested in examining longitudinal effects, or antecedents

Table 1
Descriptive statistics for perceptual speed, verbal knowledge, close visual acuity, and distance visual acuity

	Measurement occasion			
	1	2	3	4
Perceptual speed				
N	440	–	176	120
Mean/SD	50.00/10.00	–/–	53.73/9.47	54.53/9.40
Skewness/kurtosis	−0.30/−0.57	–/–	−0.78/0.20	−0.76/0.99
Verbal knowledge				
N	447	–	178	128
Mean/SD	50.00/10.00	–/–	51.86/8.68	54.37/8.50
Skewness/kurtosis	−0.51/−0.54	–/–	−0.78/0.40	−0.79/0.08
Close vision				
N	512	355	243	163
Mean/SD	50.00/10.00	47.29/8.15	48.23/8.35	49.21/8.60
Skewness/kurtosis	0.54/−0.09	0.27/−0.41	0.29/−0.37	0.22/0.09
Distance vision				
N	485	336	236	154
Mean/SD	50.00/10.00	49.44/8.47	51.93/8.51	51.41/8.03
Skewness/kurtosis	0.50/−0.65	0.86/0.73	0.34/−0.68	0.41/−0.44

Note: N=number of valid data points; SD=standard deviation.

of change. For this purpose, we examine how much each variable predicts its own change (e.g., auto-correlative effects) and how much it predicts change in the other variables (e.g., cross-lagged effects). In order to account for possible errors of measurement and differences in variables' reliability coefficients, both types of effects are explored in latent space.

The Dual Change Score Model (DCSM), originally developed by McArdle and Hamagami, is well suited for this kind of analysis (Hamagami & McArdle, 2001; Hamagami, McArdle, & Cohen, 2000; McArdle, 2001; McArdle & Hamagami, 2001; McArdle, Hamagami, Meredith, & Bradway, 2000; see also Ghisletta & Lindenberger, 2003). As a specialized longitudinal instantiation of structural equation modeling (SEM), the DCSM expands the well-established LGM (e.g., Meredith & Tisak, 1984, July; Bryk & Raudenbush, 1987; Duncan, Duncan, Strycker, Li, & Alpert, 1999; McArdle, 1986) and latent difference score models (McArdle & Hamagami, 2001; McArdle & Nesselroade, 1994).

Fig. 1 presents a diagram of a DCSM applied to a variable measured four times. The time-series is represented by the four squares marked X_1 to X_4. From this time-series unrelated variance (e.g., error) is estimated (this is represented by circles that denote E with the two-headed arrows denoted V_E). It is commonly assumed that the residual variance does neither change nor correlate with itself over time. Two latent variables are then "extracted" from the time-series, a Level factor and a Linear Slope factor (circles denote L and LS, respectively). The Level represents a person's score at the beginning of the time-series. Hence, the score X_1 is the sum of the Level factor and the residual component E. The score at X_2 is the sum of the previous score X_1 and a latent component denoted ΔX_2, which represents the reliable change between X_1 and X_2. Analogously, the DCSM defines the latent change between any two adjacent measurements. In the univariate DCSM, there are two influences on the latent change scores.

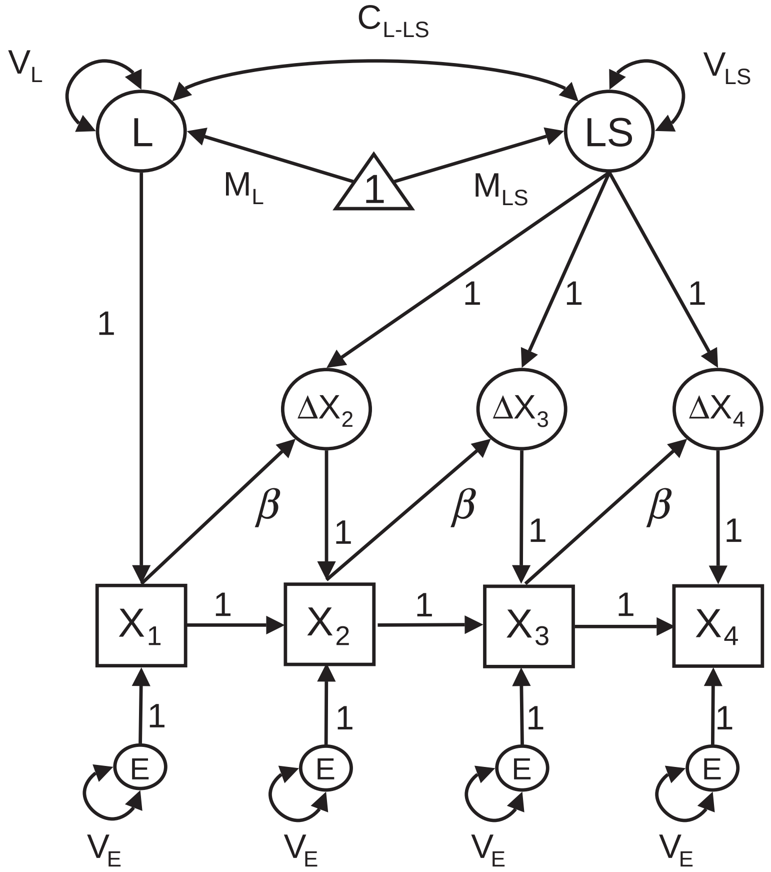

Fig. 1. Graphical representation of a univariate dual change score model estimating 7 parameters.

On the one hand the Linear Slope exerts a constant effect between any two adjacent measurements. On the other hand, the latent change scores are affected by previous measurements through the auto-proportionality, or self-feedback, effect represented by β. Because this parameter quantifies the direct effect of a previous score onto the subsequent change score it can be considered dynamic.

Both Level and Linear Slope factors are estimated at the population level (their means M_L and M_{LS} are estimated by the regression weights of a constant variable represented by the triangle denoted 1). Moreover, both Level and Linear Slope factors allow for individual differences (their variances are denoted V_L and V_{LS}, respectively) and may covary (i.e., the two-headed arrow $C_{L\text{–}\mathrm{LS}}$).

It follows that a standard LGM can be construed as a DCSM where β is equal to zero. Conversely, for the general case (i.e., when the beta of the DCSM is not equal to zero), the Linear Slopes of a standard LGM and DCSM differ in meaning. In a standard LGM change is affected solely by the Linear Slope, whereas in the univariate DCSM change is also affected by the latent Level of the preceding measurement occasion. Because the LGM (estimating six parameters) is nested within the DCSM (which estimates seven parameters) the two models can be statistically compared to evaluate whether inclusion of the auto-proportional β parameter is associated with superior model fit. The parameter β may vary in time, but is here assumed with the same magnitude between any two waves (this assumption is testable in principle but requires a higher measurement density than available in BASE). Moreover, we assume the parameter β to be fixed, that is, with the same value for all participants. In its current specification, the DCSM does not estimate individual differences in dynamic parameters. However, individual differences in Level, Linear Slope, and Error are estimated and contribute to generate a population of longitudinal curves.

Just like multivariate extensions of LGMs and longitudinal multilevel models are easily possible (e.g., MacCallum, Kim, Malarkey, & Kiecolt-Glaser, 1997; McArdle, 1986; Raudenbush & Chan, 1992; Stoolmiller, 1994), so are multivariate extensions of DCSMs. Multivariate LGMs allow for the study of correlated individual differences in Levels and Slopes of more than one variable. Hence, a common specification of the bivariate LGM estimates twice the six parameters of each time series plus 4 correlations among the Levels and Slopes of the two variables, for a total of 16 parameters. However, the static structures of interindividual differences effects, although informative, do not represent directional influences that variables might exert on each other. In contrast, multivariate DCSMs allow for such directional, time-lagged effects. Analogous to the intra-variable auto-proportional β parameter, an inter-variable cross-lagged γ parameter represents the direct effect that a variable at time t exerts on the change in another variable occurring between times t and $t+1$.

Fig. 2 depicts a bivariate DCSM, where for simplification paths with fixed values of 1 are not labeled. Variable X was measured four times, while variable Y was not assessed during the second wave (e.g., X could be close visual acuity and Y could be perceptual speed in this application). Therefore the second measurement of Y is represented by a circle, identifying its latent status during that wave (as in McArdle et al., 2000). The inclusion of such a “node” variable (Horn & McArdle, 1980) allows for the proper estimation of change parameters despite of an actual measurement interruption in the change process. The two variables are interrelated via the four correlations among the Level and Linear Slope factors as well as via the two latent cross-lagged parameters denoted γ_X and γ_Y. The two parameters (assumed invariant between any two waves) directly assess the effect that variable X exerts on the upcoming change in Y and the effect that variable Y exerts on the upcoming change in X. The bivariate DCSM estimates the same 16 parameters of a bivariate LGM plus 2 β parameters and 2 γ parameters, for a total of 20 parameters. Analogously to β, individual differences in the γ parameter are not estimated.

The effects of time-invariant covariates, such as chronological age at the beginning of the study, can also be assessed. Fig. 3 depicts a bivariate DCSM with chronological age as a covariate (paths with fixed values of 1 are again not labeled for simplification). In this application we are interested in the effects that chronological age at time 1 exerts on Level scores (estimated at time 1) and on the latent change scores (i.e., are one’s score at the beginning of the study and one’s change throughout the study predictable from age?). The effects of age, of great importance in age-heterogeneous studies such as the BASE, are denoted in Fig. 3 by the thick one-headed arrows. We assume the effects of age at time 1 on the latent change scores of each variable examined to be constant in time, although this is an empirical, testable assumption. In addition to the 20 parameters of a bivariate DCSM, this model also estimates the mean and variance of age as well as the two regression effects of age on the Level factors and the two regression effects of age on the change scores.

In the end, three effects of interest can be assessed with this expanded DCSM: (a) the effect that chronological age exerts on the Level and latent change scores of variable X (or Y); (b) independent of chronological age, the effect that variable X (or Y) exerts on its own latent change scores; (c) independent of chronological age and the auto-proportional prediction, the effect that variable X (or Y)

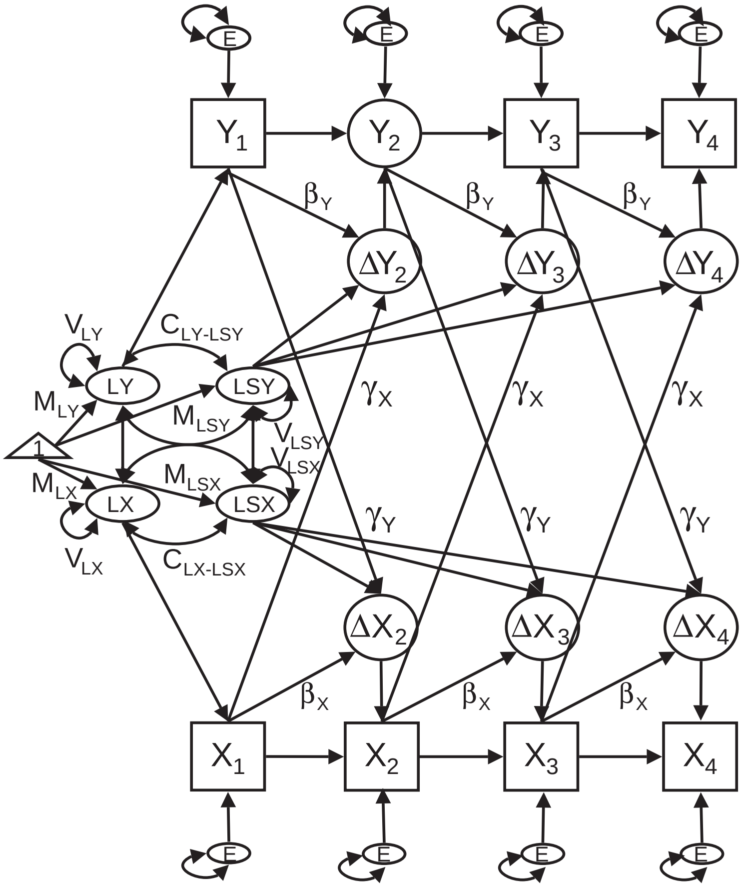

Fig. 2. Graphical representation of a bivariate dual change score model estimating 20 parameters.

exerts on the latent change scores of variable Y (or X). Setting all dynamic parameters (i.e., the auto-proportion β and the cross-lagged γ) to zero reduces the bivariate DCSM to a bivariate LGM with chronological age as covariate. Given that the bivariate LGM is nested within the bivariate DCSM the statistical test of the dynamic parameters is feasible. For further detail on DCSMs described here as well as variations and extensions, see McArdle et al. (2000), McArdle and Hamagami (2001), McArdle et al. (2004), McArdle (2001), Hamagami et al. (2000), Hamagami and McArdle (2001) and Ghisletta and Lindenberger (2003).

For simplicity and space reasons the diagrams are limited to the bivariate case. The application reported in this article, though, involves four variables. The extension from the bivariate case to the quadrivariate case is straightforward and is directly generalizable. For all computations we utilized Mx (Neale, Boker, Xie, & Maes, 1999) and AMOS (Arbuckle & Wothke, 1999). We consistently obtained full estimation agreement between the two softwares, within rounding errors. To judge the feasibility of the models and to compute nested model comparisons we used the chi-square index, the Root Mean Square Error of Approximation (RMSEA; Steiger & Lind, 1980, June) with its 95% confidence interval, and Akaike's Information Criterion (AIC, Akaike, 1987). Because of the unbalanced data situation, the chi-square

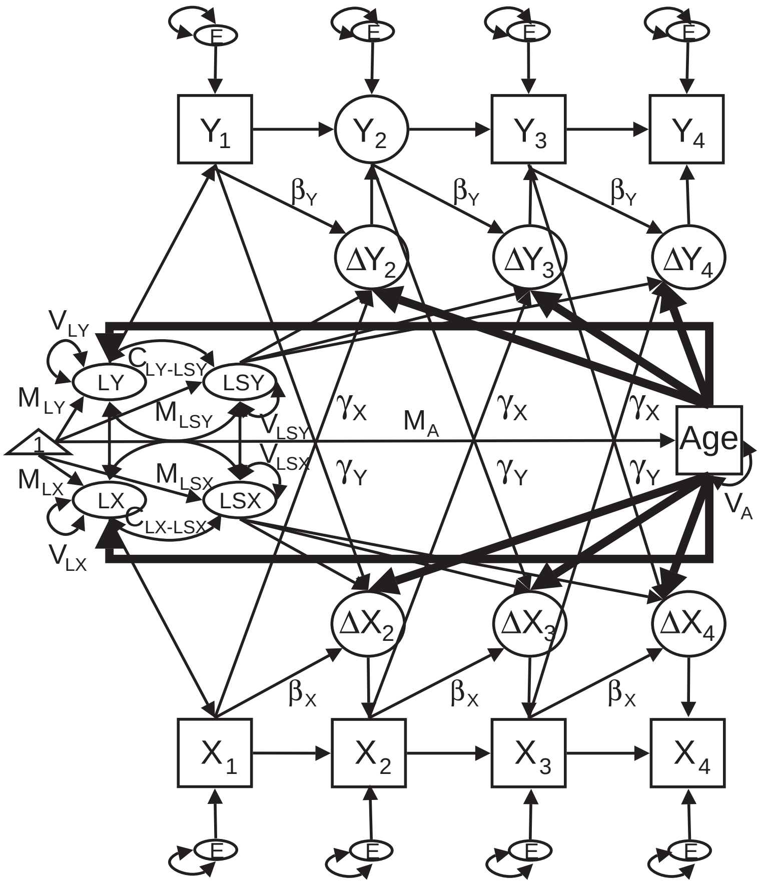

Fig. 3. Graphical representation of a bivariate dual change score model with chronological age as covariate estimating 26 parameters.

index cannot be computed directly. Instead, the log likelihood (−2LL) is provided. By comparing a model's −2LL to the −2LL of the saturated model (when this can be estimated) the computation of the model's chi-square fit value is directly possible (Arbuckle & Wothke, 1999).

Incomplete data were not replaced by imputed data, nor were the participants with incomplete data eliminated from the present analyses.[2] Instead, we used the Raw Maximum Likelihood (Arbuckle, 1996; McArdle, 1994) estimation algorithm, introduced by Lange, Westlake, and Spence (1976) in the context of pedigree analysis. This algorithm relies on the missing at random assumption (MAR; Rubin, 1974) and produces unbiased estimates if missing information is either completely at random or dependent on variables included in the statistical model (which in the longitudinal setting usually includes previous measurements of the same variable). Clearly, intellectual and sensory data in samples of very old individuals are not missing completely at random. However, there is a high dependency between the

[2] We did however run all analyses on the subsample with complete-data only ($N = 120$) to check for selectivity. As shown later on, no meaningful differences in results were obtained between the full sample and the complete-data subsample.

reason for missing intellectual and sensory information (e.g., dropout, mortality, disease) and previous scores on those variables as well as age (cf. Lindenberger, Singer, & Baltes, 2002; Singer et al., 2003). Our modeling procedure includes hence important predictors of data incompleteness (i.e., previous scores and age). The bias in the final parameters should therefore be reduced. More importantly, it is difficult to conceive how dynamic parameters should be inflated by data incompleteness.

4. Results

We present our results in three sections. The first section presents the detailed findings of quadrivariate LGMs without and with statistical control for chronological age. The second section presents the detailed results of the quadrivariate DCSMs, again with and without statistical control for chronological age. The third and final sections present the summary fit indices of two multivariate DCSMs nested within the full DCSM with statistical control for age. These nested statistical comparisons address general hypotheses about dynamic relations among the four intellectual and sensory variables examined.

4.1. Multivariate LGMs

Table 2 presents the parameter estimates and fit indices of the two quadrivariate LGMs (QLGMs), the former without and the latter with statistical control for chronological age. Before presenting the results in details, we must report a set of parameters constraints we imposed on both models. When we first tested

Table 2
Quadrivariate latent growth models parameter estimates and model fit indices without (upper panel) and with (lower panel) control for age

Parameter	Composite score			
	PS	VK	CV	DV
Mean level	49.02 (0.48)	49.25 (0.47)	49.42 (0.41)	49.31 (0.43)
Mean linear slope	−1.82 (0.19)	−0.31 (0.15)	−2.25 (0.19)	−0.67 (0.20)
Var. level	99.09 (7.20)	85.15 (6.50)	68.55 (5.63)	59.14 (6.03)
Var. linear slope	4.81 (0.80)	@0	5.16 (1.03)	2.63 (1.16)
Var. uniqueness	8.27 (1.11)	16.82 (1.38)	23.77 (1.50)	37.52 (2.37)
Mean level	48.93 (0.39)	49.21(0.44)	49.48 (0.36)	49.25 (0.35)
Mean linear slope	−2.09 (0.18)	−0.30 (0.15)	−2.58 (0.18)	−0.82 (0.20)
Var. level	60.80 (4.75)	73.10 (5.72)	48.42 (4.39)	29.49 (4.25)
Var. linear slope	3.91 (0.72)	@0	4.72 (0.97)	2.53 (1.15)
Var. uniqueness	8.36 (1.12)	16.83 (1.38)	23.48 (1.47)	37.26 (2.35)
Age $\rightarrow L$	−0.72 (0.04)	−0.40 (0.05)	−0.51 (0.04)	−0.64 (0.04)
Age $\rightarrow \Delta$	−0.13 (0.02)	@0	−0.09 (0.02)	ns

Note: PS = perceptual speed; VK = verbal knowledge; CV = close visual acuity; DV = distance visual acuity; Var. = variance; Age $\rightarrow L$ = effect of chronological age on Level; Age $\rightarrow \Delta$ = effect of chronological age on Change; values in parentheses are standard errors; the mean Level refers to level of functioning at occasion 1; @0 means constrained to 0; ns = not significant at $\alpha = 0.05$.
Fit indices without control for age: $\chi^2(N = 516;\ df = 79) = 217.90$. RMSEA = 0.058 (95% CI = 0.047 to 0.069), AIC = 297.90.
Fit indices with control for age: $\chi^2(N = 516;\ df = 86) = 218.13$. RMSEA = 0.055 (95% CI = 0.044 to 0.065), AIC = 316.13.

the QLGM without control for age, we obtained that the variance of linear change in verbal knowledge was not significant. However, the QLGM with control for age obtained that age was a predictor of linear change in verbal knowledge. The two results are paradoxical, because the lack of linear change variance in the former QLGM should mean that no significant predictor of linear change exists in the latter QLGM. To proceed systematically in our modeling strategy and to avoid inconsistent outcomes we decided to run both QLGMs with a set of parameter constraints on the Linear Slope of verbal knowledge. We constrained the variance of the Linear Slope of verbal knowledge to zero. As a consequence, we also constrained all related covariances and, in the QLGM with control for age, the regression from age to the Linear Slope of verbal knowledge. These constraints are indicated by the symbol '@0' in Table 2.

Under these conditions, both models obtained decent fits ($\chi^2(N=516;\ df=79)=217.90$, RMSEA=0.058 (95% CI=0.047 to 0.069), AIC=297.90 without control for age, $\chi^2(N=516;\ df=86)=218.13$, RMSEA=0.055 (95% CI=0.044 to 0.065), AIC=316.13 with control for age).[3] Both RMSEA indices were below 0.08, indicating acceptable fit, while their 95% confidence intervals contained 0.05, indicating that one cannot reject close fit to the data. The AIC favors the model not controlling for age but the inclusion of chronological age yields estimates of change parameters that are less affected by shared age trends. Indeed, the negative means of the change factors of all variables increased in magnitude when age differences were removed (the means of the Level factors remained virtually unchanged because age was centered around its sample mean). Specifically, for perceptual speed, verbal knowledge, close vision, and distance vision the average yearly decline increased from 1.82, 0.31, 2.25, and 0.67 to 2.09, 0.30, 2.58, and 0.82, respectively.[4]

Age accounted for considerable amounts of Level variance. For perceptual speed, the Level variance diminished from 99.09 to 60.80 when including age, which corresponds to explaining 38.64% of the Level variance. The analogous percentages for verbal knowledge, close vision, and distance vision were 14.15, 29.37, and 50.16, respectively.[5] This was confirmed by the highly reliable regression weights of age on each Level factor. For perceptual speed, being one year older represented a Level score disadvantage of 0.72 T-units. The analogous regression weights for verbal knowledge, close vision, and distance vision were -0.40, -0.51, and -0.64, in that order.[6]

Age also affected variance in change in perceptual speed and close vision: 18.71% of the variance in change in perceptual speed and 8.53% for close vision was accounted for by age[7] (the decrease of 3.80%[8] for distance vision was not significant, given that the regression weight from age to linear change

[3] Without the set of constraints imposed on the verbal knowledge linear change factor, the two models fitted the data similarly well: $\chi^2(N=516;\ df=71)=177.81$, RMSEA=0.054 (95% CI=0.042 to 0.066), AIC=73.81 without control for age, $\chi^2(N=516;\ df=77)=178.40$, RMSEA=0.051 (95% CI=0.039 to 0.062), AIC=294.40 with control for age.

[4] Without the set of constraints imposed on the verbal knowledge linear change factor, the control for age has similar effects on these regression weights. Indeed, they change from 1.85, 0.80, 2.23, and 0.67 to 2.13, 0.98, 2.56, and 0.82 for perceptual speed, verbal knowledge, close vision, and distance vision, respectively.

[5] Without the set of constraints imposed on the verbal knowledge linear change factor, these percentages are very similar: 38.49%, 11.66%, 29.41%, and 50.12% for perceptual speed, verbal knowledge, close vision, and distance vision, respectively.

[6] Without the set of constraints imposed on the verbal knowledge linear change factor, these regression weights are virtually identical: -0.72, -0.37, -0.52, and -0.64 for perceptual speed, verbal knowledge, close vision, and distance vision, respectively.

[7] Without the set of constraints imposed on the verbal knowledge linear change factor, these percentages are virtually identical: 17.99% for perceptual speed and 8.80% for close vision.

[8] 4.76% in the model without the constraints on the verbal knowledge linear change factor.

Table 3
Covariances and standard errors from quadrivariate latent growth models—lower diagonal without control for age, upper diagonal with control for age

	L_{PS}	L_{VK}	L_{CV}	L_{DV}	LS_{PS}	LS_{VK}	LS_{CV}	LS_{DV}
L_{PS}	–	**43.31**	**24.56**	**18.84**	0.92	na	−0.76	−1.42
	–	(4.15)	(3.38)	(3.13)	(1.55)	na	(1.56)	(1.67)
L_{VK}	**64.75**	–	**22.40**	**14.71**	1.96	na	−2.16	−0.44
	(5.66)	–	(3.67)	(3.39)	(1.60)	na	(1.70)	(1.81)
L_{CV}	**52.04**	**37.79**	–	**21.83**	2.29	na	**−9.07**	−1.74
	(5.04)	(4.60)	–	(3.04)	(1.44)	na	(1.77)	(1.60)
L_{DV}	**52.72**	**33.64**	**46.25**	–	0.36	na	**−3.86**	**−4.34**
	(5.13)	(4.59)	(4.49)	–	(1.34)	na	(1.41)	(1.89)
LS_{PS}	**6.53**	**4.76**	**6.34**	**5.48**	–	na	**1.41**	**1.53**
	(1.99)	(1.81)	(1.75)	(1.75)	–	na	(0.58)	(0.61)
LS_{VK}	na	na	na	na	na	–	na	na
	na	na	na	na	na	–	na	na
LS_{CV}	2.59	−0.76	**−6.75**	−0.73	**1.97**	na	–	**2.42**
	(2.01)	1.88	(1.98)	1.79	(0.64)	na	–	(0.70)
LS_{DV}	**−4.17**	−2.32	**−3.71**	**−6.56**	1.07	na	**2.18**	–
	(2.09)	1.96	(1.86)	(2.23)	0.64	na	(0.72)	–

Note: L=Level; LS=Linear Slope; PS=perceptual speed; VK=verbal knowledge; CV=close visual acuity; DV=distance visual acuity; covariances were estimated at occasion 1; significant covariances at $\alpha=0.05$ are boldfaced; na=not applicable: covariances with Linear Slope of verbal knowledge are not defined, hence constrained to 0, because the variance of Linear Slope of verbal knowledge was not reliable; variances are shown in Table 2.

in distant vision was 0). Being one year older was associated with an acceleration of negative change of 0.13 T-units for perceptual speed and 0.09 for close vision.[9]

Table 3 presents the covariances with their standard errors and Table 4 the correlations among the Level and Linear Slope components of the QLGMs. In both tables, covariances and standard errors or correlations not controlling for age are shown below and covariances and standard errors or correlations controlling for age are shown above the main diagonal. To some extent, covariances and correlations among Levels were reduced in magnitude after controlling for age. Confirming cross-sectional findings of BASE, perceptual speed correlated more highly with the sensory composites than verbal knowledge did (cf. Baltes & Lindenberger, 1997; Lindenberger & Baltes, 1994). In general the correlations among the Linear Slopes were much weaker than those among the Levels when not controlling for age. Indeed, two of the three possible Linear Slopes correlated (for verbal knowledge no reliable variance in Linear Slope was detected, so that the correlations with its Linear Slope were not defined and constrained to 0 as indicated above).

4.2. Multivariate DCSMs

Table 5 presents the parameter estimates, standard errors, and fit indices of the quadrivariate DCSM (QDCSM) without control for age. Although some elements of this model were similar to elements of the previous QLGMs, the interpretation becomes more complex. Indeed, the expectations about change in a

[9] These figures are the same within two decimals in the model without constraints imposed on the verbal knowledge linear change factor.

Table 4
Correlations from quadrivariate latent growth models—lower diagonal without control for age, upper diagonal with control for age

	L_{PS}	L_{VK}	L_{CV}	L_{DV}	LS_{PS}	LS_{VK}	LS_{CV}	LS_{DV}
L_{PS}	1.00	**0.65**	**0.45**	**0.44**	0.06	na	−0.04	−0.11
L_{VK}	**0.70**	1.00	**0.38**	**0.32**	0.12	na	−0.12	−0.03
L_{CV}	**0.63**	**0.49**	1.00	**0.58**	0.17	na	**−0.60**	−0.16
L_{DV}	**0.69**	**0.47**	**0.73**	1.00	0.03	na	**−0.33**	**−0.50**
LS_{PS}	**0.30**	**0.24**	**0.35**	**0.32**	1.00	na	**0.33**	**0.49**
LS_{VK}	na	na	na	na	na	1.00	na	na
LS_{CV}	0.11	−0.03	**−0.36**	−0.04	**0.40**	na	1.00	**0.70**
LS_{DV}	**−0.26**	−0.15	**−0.28**	**−0.53**	0.30	na	**0.59**	1.00

Note: L = Level; LS = Linear Slope; PS = perceptual speed; VK = verbal knowledge; CV = close visual acuity; DV = distance visual acuity; correlations were estimated at occasion 1; significant correlations at $\alpha = 0.05$ are boldfaced; na = not applicable: Correlations with Linear Slope of verbal knowledge are not defined, hence constrained to 0, because the variance of Linear Slope of verbal knowledge was not reliable.

DCSM are additive and compound and not simply constant as in a LGM, because change now consists of more than a linear addition for each unit of time elapsed. Instead, in the univariate DCSM, change is represented as the sum of two components: (a) the linear portion, represented by the conventional Linear Slope, and (b) the feedback portions of change, represented by the auto-proportional component (the previous state of that variable multiplied by the β parameter). In a multivariate specification, there are three distinct types of effects on change in each variable: (a) each variable's time-invariant Linear Slope; (b) each variable's time-dependent, self-feedback effect (i.e., via the β parameter); and (c) the time-dependent, cross-lagged effects of the remaining variables on each variable's change scores (i.e., via the γ parameters).

Compared to the first QLGM, not controlling for age, represented in the upper portion of Table 2, this model estimated 16 additional, dynamic parameters (4 β's and 12 γ's) and 8 parameters concerning the relaxation of the previous constraints on the verbal knowledge Linear Slope parameters (1 variance and 7

Table 5
Quadrivariate dual change score model parameter estimates and model fit indices without control for age

Parameter estimates	Composite score			
	PS	VK	CV	DV
Mean level	48.95 (0.47)	49.42 (0.47)	49.50 (0.44)	50.04 (0.44)
Mean linear slope	ns	54.64 (10.95)	52.67 (21.84)	ns
Var. level	98.51 (7.11)	89.62 (6.81)	61.53 (6.36)	78.36 (6.38)
Var. linear slope	ns	190.55 (42.34)	ns	ns
Var. uniqueness	7.55 (1.09)	14.02 (1.29)	21.43 (1.49)	35.00 (2.42)
β	−0.98 (0.22)	−1.55 (0.21)	−0.71 (0.11)	−0.61 (0.25)
$\gamma_{PS} \rightarrow \Delta$	–	ns	0.35 (0.16)	ns
$\gamma_{VK} \rightarrow \Delta$	ns	–	ns	ns
$\gamma_{CV} \rightarrow \Delta$	1.20 (0.44)	ns	–	ns
$\gamma_{DV} \rightarrow \Delta$	ns	ns	0.38 (0.15)	–

Note: $\chi^2(N = 516; df = 55) = 75.30$, RMSEA = 0.027 (95% CI = 0.000 to 0.043), AIC = 203.30; PS = perceptual speed; VK = verbal knowledge; CV = close visual acuity; DV = distance visual acuity; Var. = variance; β = auto-proportion parameter; $\gamma_{PS} \rightarrow \Delta$ = latent cross-lagged effect of perceptual speed on latent change scores; values in parentheses are standard errors; the mean Level refers to level of functioning at occasion 1; ns = not significant at $\alpha = 0.05$.

Table 6
Quadrivariate dual change score model parameter estimates and model fit indices with control for age

Parameter estimates	Composite score			
	PS	VK	CV	DV
Mean level	48.87 (0.39)	49.37 (0.45)	50.04 (0.39)	49.45 (0.38)
Mean linear slope	ns	52.54 (11.28)	ns	44.43 (18.82)
Var level	60.73 (4.69)	78.12 (6.10)	55.39 (4.98)	36.73 (4.89)
Var linear slope	ns	174.77 (30.97)	8.61 (3.01)	ns
Var uniqueness	7.74 (1.04)	14.01 (1.37)	21.43 (1.46)	34.07 (2.47)
Age $\rightarrow L$	-0.71 (0.05)	-0.39 (0.05)	-0.55 (0.05)	-0.62 (0.04)
Age $\rightarrow \Delta$	ns	-0.66 (0.25)	ns	ns
β	-0.69 (0.24)	-1.55 (0.19)	-0.72 (0.10)	-0.59 (0.22)
$\gamma_{PS} \rightarrow \Delta$	–	ns	0.28 (0.14)	0.84 (0.35)
$\gamma_{VK} \rightarrow \Delta$	ns	–	ns	-1.35 (0.64)
$\gamma_{CV} \rightarrow \Delta$	0.90 (0.40)	ns	–	ns
$\gamma_{DV} \rightarrow \Delta$	ns	ns	0.30 (0.13)	–

Note: $\chi^2(N=516; df=61)=84.62$, RMSEA=0.027 (95% CI=0.002 to 0.043); AIC=232.62; PS=perceptual speed; VK=verbal knowledge; CV=close visual acuity; DV=distance visual acuity; Var.=variance; Age$\rightarrow L$=effect of chronological age on Level; Age$\rightarrow\Delta$=effect of chronological age on latent change scores; β=auto-proportional parameter; $\gamma_{PS}\rightarrow\Delta$=latent cross-lagged effect of perceptual speed on latent change scores; values in parentheses are standard errors; the mean Level refers to occasion 1; ns=not significant at $\alpha=0.05$.

covariances). The model fit indices ameliorated drastically: the χ^2 diminished from 217.90 for 79 *df* to 75.30 for 55 *df*; the RMSEA diminished from 0.058 to 0.027 and its confidence interval included 0, indicating a good fit; lastly, the AIC diminished from 297.90 to 203.30. This difference in fit can be compared statistically because the two models are nested. We express the difference in fit in a comparison RMSEA (cRMSEA), which expresses the misfit between the two nested models. If the cRMSEA is 0.05 or less the misfit is negligible, meaning that from a statistical viewpoint both models describe the structure of the data equally well. A confidence interval including 0.05 means that the two models are close in misfit. In this case, although there is a significant difference in fit between the two models, we can say that they fit the data almost equally well (Browne & DuToit, 1992). When not controlling for age we obtained a cRMSEA of 0.098 with a 95% CI of [0.080–0.117].[10]

Each self-feedback β parameter resulted statistically reliable and negative. Hence, the higher the previous score of a variable, the lower the subsequent change score. These hampering auto-proportional effects, invariant across all participants, outweigh the positive average Linear Slope of verbal knowledge and close vision, resulting in an overall decreasing trend. However, the cross-variables effects must be considered simultaneously when interpreting these results. Without controlling for age, only three γ parameters resulted significant: the effects of perceptual speed, close vision, and distance vision on the changes in close vision, perceptual speed and again close vision, respectively. This dynamic system is complex and hard to interpret. Nevertheless, its statistic validity proved superior to the previous QLGM.

In the previous LGM analyses we controlled for age to obtain more valid estimates of change. Similarly, Table 6 presents the parameter estimates, standard errors, and fit indices of the QDCSM with

[10] This increase in fit is not due to the restrictions imposed on the QLGM. Indeed, the QLGM without restrictions on the Linear Slope of verbal knowledge also fitted the data considerably worse than this QDCSM (cRMSEA=0.102, 95% CI=[0.080–0.125]).

control for age. This QDCSM fitted the data well. The χ^2 value was 84.62 for 61 *df*, the RMSEA was 0.027 (95% CI=[0.002–0.043]), and the AIC was 232.62. The model fitted the data considerably better than its QLGM counterpart controlling for age (cRMSEA=0.092, 95% CI=[0.074–0.110]).[11]

This model is not statistically nested in the QDCSM not controlling for age, so that we cannot compare their fits directly. One can, however, rely on the AIC for comparison of non-nested models, which here results in preferring the model without control for age. Yet we retained the model with control for age for substantive reasons: we wanted to isolate the dynamic effects of the system from possible shared age effects. Moreover, chronological age is a strong predictor of data incompleteness, so that including it in the model satisfies to a greater degree the MAR assumption.

The mean Level estimates remained virtually unchanged at 48.87, 49.37, 50.04, and 49.45 for perceptual speed, verbal knowledge, close vision, and distance vision, respectively (chronological age was again centered around the sample mean at occasion 1). Age affected all Level scores negatively, as expected. Participants one year older were on average 0.71, 0.39, 0.55 and 0.62 T-units lower in perceptual speed, verbal knowledge, close, and distance visual performance, in that order. Note that confirming cross-sectional findings of BASE, and more generally in accordance with two-component theories of lifespan cognition, perceptual speed obtained the strongest negative age-gradient, and verbal knowledge the mildest.

The reliable γ parameters of the previous analysis were again significant when controlling for age. In addition, the cross-lagged effects from previous states in both perceptual speed and verbal knowledge on changes in distance vision were reliable in this analysis. These two effects are then propagated to the change in close vision through the significant γ parameter between previous states in distance vision and changes in close vision. As a consequence, in this model the means of Linear Slope for both close and distance vision were different from their means when not controlling for age.

The interpretation of the parameters of a QDCSM accounting for age is not simple. To ease the interpretation of the model's predictions, Fig. 4 displays the expected longitudinal mean trajectories for perceptual speed, verbal knowledge, close visual acuity, and distance visual acuity. The longitudinal expectations are quite different for the four variables. As expected in this age range, the average decrease for perceptual speed and close visual acuity is more marked than for verbal knowledge and distance visual acuity. This further confirms that the same-domain indicators (perceptual speed and verbal knowledge for cognition and close vision and distance vision for sensory functions) should not have been aggregated in these data.

By applying common tracing rules for SEMs we can write the mathematical expression of the expected change occurring between any two adjacent occasions t and $t-1$ for each variable. The equations for the latent change scores (Δ) in perceptual speed (PS), verbal knowledge (VK), close visual acuity (CV), and distance visual acuity (DV), respectively, are:

$$\Delta \mathrm{PS}_t = (-0.69)\cdot \mathrm{PS}_{t-1} + (0.90)\cdot \mathrm{CV}_{t-1} \tag{1}$$

$$\Delta \mathrm{VK}_t = (52.54) + (-0.66)\cdot \mathrm{Age} + (-1.55)\cdot \mathrm{VK}_{t-1} \tag{2}$$

$$\Delta \mathrm{CV}_t = (-0.72)\cdot \mathrm{CV}_{t-1} + (0.28)\cdot \mathrm{PS}_{t-1} + (0.30)\cdot \mathrm{DV}_{t-1} \tag{3}$$

$$\Delta \mathrm{DV}_t = (44.43) + (-0.59)\cdot \mathrm{DV}_{t-1} + (0.84)\cdot \mathrm{PS}_{t-1} + (-1.35)\cdot \mathrm{VK}_{t-1}. \tag{4}$$

[11] This increase in fit is not due to the restrictions imposed on the QLGM. Indeed, the QLGM without restrictions on the Linear Slope of verbal knowledge also fitted the data considerably worse than this QDCSM (cRMSEA=0.097, 95% CI=[0.075–0.120]).

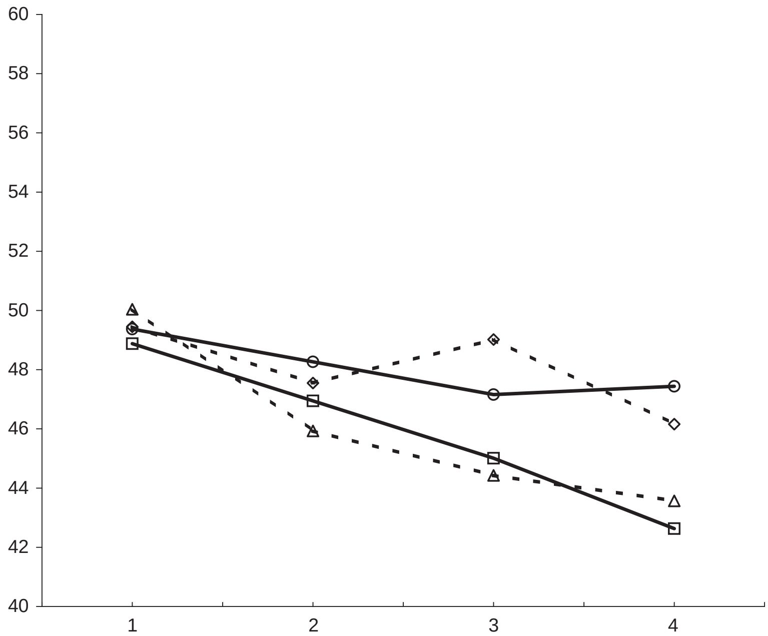

Fig. 4. Predicted population means for perceptual speed (continuous line with squares), verbal knowledge (continuous line with circles), close visual acuity (dashed line with triangles), and distance visual acuity (dashed line with diamonds) by occasion. Expectations refer to the Quadrivariate Dual Change Score Model with control for cross-sectional, occasion 1 age differences.

Both verbal knowledge and distance visual acuity are quite stable across the four occasions of measurement (cf. Fig. 4). The stability portion is represented in the equation by the mean of Linear Slope (52.54 for verbal knowledge, 44.43 for distance vision). This linear change component counteracts for verbal knowledge the effects of cross-sectional age and decreasing verbal knowledge, and for distance vision the effects of decreasing distance vision, perceptual speed, and verbal knowledge. The expected change equations for perceptual speed and close vision do not contain the mean of the Linear Slope, and hence these longitudinal trajectories are less stable. Of greater interest is the fact that (a) cross-sectional age (i.e., interindividual differences in age at the first measurement) does not affect the change in every variable; (b) although all self-feedback effects are significant, the change in each variable is affected by other variables; and (c) the dynamic effects are not limited to domain-specific influences.

Table 7 presents the covariances and standard errors and Table 8 the correlations among the Level and Linear Slope components of the QDCSM, not controlling for age in the lower diagonal, controlling for age in the upper diagonal. Similarly to results of the two QLGMs, all Level components correlated rather highly when age was not accounted for and these correlations diminished but persisted when age was included in the longitudinal modeling. However, the Linear Slopes did not correlate at all. Indeed, in this analysis it was not the static Linear Slopes that established the links among the evolutions of the variables considered. Rather, the dynamic cross-lagged proportional effects defined the relations among the change in the variables.

Table 7
Covariances and standard errors from quadrivariate dual change score models — upper diagonal with control for age, lower diagonal without control for age

	L_{PS}	L_{VK}	L_{CV}	L_{DV}	$\mathrm{LS}_{\mathrm{PS}}$	$\mathrm{LS}_{\mathrm{VK}}$	$\mathrm{LS}_{\mathrm{CV}}$	$\mathrm{LS}_{\mathrm{DV}}$
L_{PS}	–	**44.63**	**25.05**	**21.60**	na	**59.56**	1.03	na
	–	(4.28)	(3.56)	(3.34)	na	(12.01)	(6.18)	na
L_{VK}	**65.13**	–	**23.87**	**18.50**	na	**111.49**	8.07	na
	(5.75)	–	(4.04)	(3.76)	na	(12.12)	(11.22)	na
L_{CV}	**53.68**	**36.71**	–	**23.90**	na	**33.92**	**8.98**	na
	(5.18)	(4.82)	–	(3.46)	na	(11.55)	(4.18)	na
L_{DV}	**54.22**	**39.51**	**48.99**	–	na	**19.20**	−0.68	na
	(5.30)	(5.00)	(4.88)	–	na	(8.04)	(3.99)	na
$\mathrm{LS}_{\mathrm{PS}}$	na	na	na	na	–	na	na	na
	na	na	na	na	–	na	na	na
$\mathrm{LS}_{\mathrm{VK}}$	**88.01**	**126.10**	**46.46**	**56.54**	na	–	12.08	na
	(21.07)	(16.31)	(15.23)	(19.03)	na	–	(17.05)	na
$\mathrm{LS}_{\mathrm{CV}}$	na	na	na	na	na	na	–	na
	na	na	na	na	na	na	–	na
$\mathrm{LS}_{\mathrm{DV}}$	na	na	na	na	na	na	na	–
	na	na	na	na	na	na	na	–

Note: L=Level; LS=Linear Slope; PS=perceptual speed; VK=verbal knowledge; CV=close visual acuity; DV=distance visual acuity; covariances were estimated at occasion 1; significant covariances at $\alpha=0.05$ are boldfaced; na=not applicable; covariances with Linear Slope of perceptual speed, distance vision, and (when not controlling for age) close vision are not defined because the variances of those slopes were not reliable; variances are shown in Tables 5 and 6 resp.

4.3. Alternative dynamic hypotheses

To investigate further dynamic relations among the four variables we tested two additional models, each of which operationalized a specific hypothesis about the dynamics of the system considered. Both models were restrictions of the full QDCSM with control for age. Specifically, for each hypothesis we set a series of cross-lagged γ parameters to zero, while the remaining parameters of the QDCSM were

Table 8
Correlations from quadrivariate dual change score models—upper diagonal with control for age, lower diagonal without control for age

	L_{PS}	L_{VK}	L_{CV}	L_{DV}	$\mathrm{LS}_{\mathrm{PS}}$	$\mathrm{LS}_{\mathrm{VK}}$	$\mathrm{LS}_{\mathrm{CV}}$	$\mathrm{LS}_{\mathrm{DV}}$
L_{PS}	1.00	**0.65**	**0.43**	**0.46**	na	**0.58**	0.05	na
L_{VK}	**0.69**	1.00	**0.36**	**0.35**	na	**0.95**	0.31	na
L_{CV}	**0.69**	**0.49**	1.00	**0.53**	na	**0.34**	**0.41**	na
L_{DV}	**0.62**	**0.47**	**0.71**	1.00	na	**0.24**	−0.04	na
$\mathrm{LS}_{\mathrm{PS}}$	na	na	na	na	1.00	na	na	na
$\mathrm{LS}_{\mathrm{VK}}$	**0.64**	**0.97**	**0.43**	**0.46**	na	1.00	0.31	na
$\mathrm{LS}_{\mathrm{CV}}$	na	na	na	na	na	na	1.00	na
$\mathrm{LS}_{\mathrm{DV}}$	na	na	na	na	na	na	na	1.00

Note: L=Level; LS=Linear Slope; PS=perceptual speed; VK=verbal knowledge; CV=close visual acuity; DV=distance visual acuity; correlations were estimated at occasion 1; significant correlations at $\alpha=$ 0.05 are boldfaced; na=not applicable; Correlations with Linear Slope of Perceptual Speed, Distance Vision, and (when not controlling for age) Close Vision are not defined because the variances of those slopes were not reliable.

freely estimated (in particular all auto-regressive β parameters and all age effects). This procedure allowed us to compare directly the statistical fit of each alternative model to that of the full QDCSM, where no γ parameters were constrained to zero. We again re-expressed the comparisons in fit of the nested models as cRMSEA to address the feasibility of the parameter constraints enforced. For simplicity Table 9 only presents the statistical comparisons between each alternative model and the full multivariate QDCSM.

The first analysis examined the strength of domain-specific predictions. The corresponding hypothesis posited that the latent change scores of all variables were not affected by previous scores of the other same-domain variable. This was implemented by constraining the value of the γ parameter from perceptual speed to verbal knowledge and from verbal knowledge to perceptual speed to zero. Likewise, close and distance visual acuities were not allowed to affect each other's change components. However, across-domain dynamics were allowed. For instance, change in perceptual speed was not dependent on verbal knowledge, but could be dependent on close and distance visual acuities. We called this hypothesis "No within-domain cross-lags." Surprisingly, this hypothesis could not be rejected on statistical grounds. The drop in fit statistic was 6 χ^2 points for 4 *df*, corresponding to a cRMSEA of 0.03 (95% confidence interval = [0.00–0.09]), hence not reliable. Therefore, this model described the structure and dynamical relationships of the data as well as the full QDCSM, but with greater parsimony.

In the second analysis, we examined the strength of predictions across domains. Here, we hypothesized that the change in each variable could only be affected by the other same-domain variable, but not by variables exogenous to that domain. This hypothesis, which we called "No across-domain cross-lags," was operationalized by setting the two cross-lagged parameters from each intellectual variable on the two sensory variables to zero (i.e., γ's from PS and VK to ΔCV and to ΔDV = 0), and vice versa (i.e., γ's from CV and DV to ΔPS and to ΔVK = 0). This hypothesis was rejected on grounds of statistical comparison. The difference in fit between this and the full quadrivariate DCSM resulted in 39 χ^2 points for 8 degrees of freedom, corresponding to a cRMSEA of 0.09 (95% confidence interval = [0.06–0.12]). Clearly, we could not consider the two facets of intellectual and sensory performance, marked by these four specific tests, as independent in their evolutions. There exist reliable intersystemic dynamical relations between intellectual abilities and visual acuity.

4.4. Selectivity

To assess the degree to which our results could have been affected by sample selectivity, we performed all analyses on the subsample with complete data only (N = 120). For brevity, instead of presenting the detailed results we will only present the major findings. The main substantive results did

Table 9
Differences in fit between alternative dynamic hypotheses and the full quadrivariate dual change score model ($\chi^2(N=516; df=61)=85$)

Hypothesis	Δdf	$\Delta\chi^2$	cRMSEA	95% CI cRMSEA
1. No within-domain cross-lags	4	6	0.03	0.00 to 0.09
2. No across-domain cross-lags	8	39	0.09	0.06 to 0.12

Note: Δ = difference compared to full QDCSM; cRMSEA = Comparative Root Mean Square Error of Approximation; CI = confidence interval; both hypotheses are nested under the full QDCSM.

not change as a function of sample selectivity. In particular (a) the QDCSM described the overall structure of the data very satisfactorily, both without ($\chi^2(N=120;\ df=55)=59.76$, RMSEA=0.027 (95% CI=[0–0.071]), AIC=187.76) and with ($\chi^2(N=120;\ df=61)=68.99$, RMSEA=0.033 (95% CI=[0–0.072]), AIC=216.99) control for age; (b) the QDCSM described the overall structure of the data better than the QLGM, both without (cRMSEA=0.141, 95% CI=[0.093–0.191]) and with (cRMSEA=0.133, 95% CI=[0.084–0.184]) control for age; (c) all correlations involving Linear Slopes that were significant within the QLGMs were no longer significant with the QDCSMs; and (d) the strong intersystemic dynamic links between cognitive and sensory variables were confirmed. Indeed, the 'No within-domain cross-lags' model was close in fit to the full QDCSM (cRMSEA=0.121, 95% CI=[0–0.225]), hence was not rejectable, while the 'No across-domain cross-lags' model was rejectable when compared to the full QDCSM (cRMSEA=0.141, 95% CI=[0.073–0.212]).

As reported above, individuals with lower scores on measures of intellectual and sensory functioning and of more advanced age have been found to be less likely to continue participation in the BASE (Lindenberger et al., 2002; Singer et al., 2003). The models reported before, which were based on the full sample, including individuals who discontinued participation at later occasions, estimate effects of selective attrition to the extent that these effects are predicted by variables included in the models. For this reason, results based on the full sample are more likely to yield unbiased and efficient estimates of population parameters than models restricted to longitudinal-study survivors. Hence, the present analysis restricted to longitudinal-study survivors should not be taken as a validation of the earlier analysis. Rather, the results demonstrate that the static and dynamic variable relations identified in the total sample were also present in a highly selective subgroup of this total sample.

5. Discussion

The main goal of this work was to extend established findings on the link between intellectual and sensory domains of functioning from cross-sectional, static to longitudinal, dynamic analyses. Through systematic nested comparisons using static and dynamic variants of LGMs, we were able to show that longitudinal old-age changes in perceptual speed, verbal knowledge, close visual acuity, and distance visual acuity form a complex and dynamic multivariate system.

Four major findings emerged, and we will discuss each in turn. First, separable average longitudinal trajectories emerged for each variable considered. Average longitudinal decline for verbal knowledge was minor but statistically reliable, whereas the longitudinal decline for perceptual speed was steep. Psychometric markers indicative of Gs and psychometric markers of the pragmatics of cognition, or broad Gc (e.g., Baltes, 1987; Horn, 1989) are known to follow different longitudinal trajectories across the lifespan (Baltes et al., 1998; Horn & Hofer, 1992; Horn & Noll, 1997; Li et al., 2004; Lindenberger & Baltes, 1997; McArdle et al., 2000; McArdle & Prescott, 1992; Schaie, 1996; Singer et al., 2003; Stankov & Chen, 1988). At the same time, in very old age, trajectories representing pragmatic abilities also tend to decline, providing support for one facet of the dedifferentiation hypothesis of intellectual abilities in old age (Deary & Pagliari, 1991; Ghisletta & Lindenberger, 2003; Lindenberger & Baltes, 1994; Reinert, Baltes, & Schmidt, 1966; Schaie, 1962). In this study, mechanic and pragmatic trajectories spanned on average only six years. This relatively short longitudinal time span was sufficient to establish the pattern of differential decline predicted by two-component lifespan theories of intelligence (cf. Lindenberger, 2001).

With respect to vision, we refrained from merging close and distance visual acuity into a single visual acuity composite. Most earlier cross-sectional studies either included only one kind of visual acuity assessment (close, distance, or other), or, when available, merged multiple visual acuity assessments into a single aggregate construct. Our longitudinal results confirm that decrements are indeed greater for close acuity than for distance acuity, at least within the age period considered here (i.e., age 70 years and beyond). This divergence points to possible differences in the relative importance of various factors contributing to decrements in close and distance visual acuity. For instance, to some extent, and despite the use of corrective glasses, these differences may reflect variations in the prevalence and time course of presbyopia and myopia. Presbyopia consists in the increased rigidity of the crystalline lens, which reduces the eye's capacity to focus on very near objects; it is ameliorated by the use of convex lenses. This rather normative condition is known to affect close visual acuity by middle adulthood (Agarwal, 1947; Berens, 1947). With myopia, on the other hand, distant images are focused in front of, rather than on, the retina, again reflecting a defect in the optical properties of the lens. As a consequence, distant objects appear blurred, unless appropriate concave lenses are used. This condition is less affected by age than presbyopia. These differences in peripheral factors influencing close and distance visual acuity may have contributed to the observed differences in longitudinal trajectories.

The second major finding that emerged from this study was that static-Level links between intellectual and sensory domains persist when examined in light of longitudinal evidence, both with mainly static (standard LGM) and dynamic (DCSM) analyses. Multivariate LGMs and DCSMs separate Level variance from error variance and observed Change information. Cross-sectional analyses using SEM such as confirmatory factor analysis separate Level information from error and task-specific variance but they cannot separate Level and Change information. Thus, to the extent that the tasks used in this study are valid markers of their functional domain (e.g., Little, Lindenberger, & Nesselroade, 1999), the benefit of the present analyses consists in providing not only static and dynamic representations of Change but also more reliable and valid representations of Level. Both our LGM and DCSM results demonstrate that correlations among intellectual and sensory Level components are high, and do not primarily reflect shared mean age trends; when controlling for age at initial testing, these correlations continued to be substantial and statistically reliable. This finding confirms and extends evidence based on cross-sectional analyses of the present and comparable samples (Anstey et al., 1997, 1993; Anstey & Smith, 1999; Anstey, 1999b; Baltes & Lindenberger, 1997; Clement, 1974; Li et al., 1998; Lindenberger & Baltes, 1994; Rabbitt, 1991; Roberts et al., 1997; Schaie, 1996; Salthouse et al., 1996, 1998; Stankov, 1986; Stankov & Anstey, 1997; Stankov, Seizova-Cajić, & Roberts, 2001). In old and very old age, intellectual and sensory domains of functioning are closely related (e.g., Clark, 1960; Cohn, Dustman, & Bradford, 1984; Dirken, 1972; Heron & Chown, 1967; Lindenberger & Baltes, 1994; Welford & Birren, 1965).

Recent Monte Carlo simulations of multivariate LGMs have shown that the sampling distributions of variances and covariances of latent change, as estimated by LGMs, are influenced by measurement error (Hertzog, Lindenberger, Ghisletta, & Oertzen, submitted for publication). That is, contrary to what is generally assumed, change processes estimated by LGMs on the basis of single indicators with less than perfect reliability are not immune to quality of measurement. Sampling distributions of latent variances and covariances of change are wider with less reliable (i.e., more error-prone) measures, with the consequence that the statistical power to reject the null hypotheses of zero variance and zero covariances is reduced when reliability of measurement is low. The results of power analyses reported by Hertzog et al. (submitted for publication) also suggest that variances and covariances of change, if detected in the context of a four-occasion LGM with 516 individuals, are likely to be of moderate or large effect size, even when reliability is in the 0.90's. Based on the simulation study of Hertzog et al. (submitted for publication), we feel confident in interpreting variances and covariances in latent change that reliably differ from zero in the present set of analyses.

The third major finding concerns covariations among the Linear Change components. With the multivariate LGM, all variables but verbal knowledge displayed differential change (i.e., variance in the Linear Slope factor). Consequently, covariances among Linear Slope components of perceptual speed, close vision, and distance vision were defined in this model. When not controlling for age, all but the covariance between the change components of perceptual speed and distance vision were reliable. When controlling for age, all defined covariances were statistically different from zero. Specifically, statistically controlling for the cross-sectional portion of the age variance enhanced rather than diminished the covariance in Linear Change between perceptual speed and distance visual acuity (from $r=0.30$, $p=0.10$ to $r=0.49$, $p<0.02$, cf. Table 4). Contrary to conventional wisdom, this finding shows that presence of uncontrolled cross-sectional age variance does not necessarily lead to positively biased estimates of covariations in change.

The shift from a standard multivariate LGM to the dynamic multivariate DCSM led to a profound reorganization of change information in the system under consideration. In contrast to the standard LGM, all covariances among Linear Slope change components ceased to be statistically reliable, both with and without statistical control for age. In the quadrivariate specification of the DCSM, the Linear Slope is one of five possible change components in each variable. Given that the DCSM was superior to the corresponding LGM in statistical fit, we conclude that the results obtained with the DCSM offer a better description of the multivariate system under investigation. Based on the outcome of nested statistical comparisons, it appears that the static links among the change components of the standard LGM carried some of the dynamic effects of the dynamic DCSM. What appeared to be covariations in change with the standard LGM were shown to be more appropriately represented as directional dynamic effects in the DCSM. Although the effect sizes of the five inter-variable cross-lagged effects were not major (their standard errors in the DCSM with control for age are just slightly smaller than half the size of their point estimates), these effects, as well as the self-feedback parameters, accounted for all relations among linear change components.

The dynamics underlying the system of variables considered are not simple. Again, relations among intellectual and sensory variables considered here are free of the effects of differences in chronological age and are not biased by measurement error. By examining the individual change Eqs. (1)–(4) we can describe each variable in turn. The change in perceptual speed was reliably affected by previous scores on itself and on close vision; the change in knowledge was predicted by age, previous scores on itself, and its Linear Slope score; the change in close visual acuity was influenced by previous scores on itself, on distance vision, and on perceptual speed; and the change in distance vision was affected by previous scores on itself, on perceptual speed, on verbal knowledge, and its Linear Slope score. This series of individual descriptions speaks to the complexity of the multivariate system. Apparently, the processes underlying the longitudinal changes in the four variables considered differ from each other, yet share many components. All variables influence the change in their own scores and at least the change in one of the other three variables in the system. Perceptual speed is the only variable influencing the change in two other variables, while knowledge is the only variable whose change is not influenced by any other variable, displaying the strongest degree of dynamical independence. Two of the four statistically reliable cross-domain dynamic links referred to influences between perceptual speed and close vision.

The absence of statistically reliable within-domain links between perceptual speed and verbal knowledge seems to be inconsistent with the results of an earlier analysis on the BASE data set (Ghisletta & Lindenberger, 2003). In this earlier bivariate DCSM analysis, we found that perceptual speed strongly influenced later changes in verbal knowledge, and that verbal knowledge influenced later changes in perceptual speed, but to a lesser degree. When the two dynamic effects were directly compared, perceptual speed was found to exert a greater effect upon change on verbal knowledge than vice versa, suggesting that is was the driving force in this two-variable dynamic system. However, there are at least two differences between the present and the earlier analyses that may help in explaining the divergence in findings. First, based on the assumption of cross-sectional/longitudinal convergence (Bell, 1953), Ghisletta and Lindenberger (2003) arranged the data as a function of age instead of occasion, thereby giving greater weight to cross-sectional age trends. However, longitudinal data are needed to obtain a rejectable DCSM. Nevertheless, the results reported by Ghisletta and Lindenberger (2003) recently have been replicated in analyses on an independent, narrow-age cohort sample, accounting also for retest effects (Ghisletta & de Ribaupierre, in press). Second, in a dynamic system, any addition of a new variable may alter the dynamic influences of the other variables. In the present case, the across-domain links may have reduced some of the within-domain links to such an extent that they no longer differed from zero. Third, based on the Monte Carlo analyses reported above (i.e., Hertzog et al., submitted for publication), it needs to be stressed again that the absence of significant dynamic links must not be overinterpreted, because of possible lack of power.

In earlier confirmatory factor analyses of first-wave cross-sectional data from the BASE (e.g., Lindenberger & Baltes, 1994, 1997), it was found that perceptual speed was more closely associated with close vision than with other intellectual abilities. The presence of reciprocal time-lagged effects confirms and extends these earlier findings. Possible explanations, which are not mutually conclusive, refer to common task demands (e.g., a need to vigilantly inspect visual stimuli, perhaps favoring an effect from perceptual speed on close visual acuity) and common neural processes (e.g., loss of fine-grain resolution, similar to losses in contrast sensitivity, perhaps favoring an effect from close visual acuity on perceptual speed).

Finally, the last major finding concerns the two alternative hypotheses tested via a model-comparison strategy. Contrary to our expectations, the "No within-domain cross-lags" hypothesis was not rejected on statistical grounds. The empirical evidence presented here could not reject a DCSM in which change in intellectual and sensory markers was not predicted by same-domain variables, while change was predicted by age and previous scores on the variables from the other domain. Therefore, both intellectual and both sensory variables did not display reliable domain-specific dynamic relations. Given the low power of multivariate LGMs to detect associations among latent changes (Hertzog et al., submitted for publication), we refrain from interpreting the absence of within-domain dynamic couplings. At the same time the "No across-domain cross-lags" hypothesis was statistically rejected. This second hypothesis posited that change in the cognitive variables was not affected by previous scores on the vision variables and change in the vision variables was not affected by previous scores on the cognitive variables. Thus, statistical rejection of this hypothesis speaks in favor of the intellectual variables affecting change in the sensory variables, and the sensory variables affecting change in the intellectual variables.

Our findings provide more than a longitudinal replication of relevant cross-sectional work. They furthermore establish a stronger link between intellectual and sensory domains because the observed inter-domain associations were (a) unbiased by measurement error, (b) longitudinal, (c) directional, and (d) independent of individual differences in chronological age at baseline. Thus, the dynamic links between intellectual and sensory functioning observed in this study cannot be dismissed as statistical byproducts of functionally disconnected but age-linked processes.

In the following, we discuss the present findings in light of the three theoretical hypotheses about the strong connection between intellectual and sensory domains mentioned in the Introduction: (a) biomarker mediation (Anstey, 1999a), (b) common cause (Lindenberger & Baltes, 1994), and (c) cascade (Birren, 1964). We do not assume that the present results permit unequivocal and categorical rejection of any of these three hypotheses. Rather, as we will argue below, these hypotheses differ in consistency with our findings as a matter of degree.

The mediation hypothesis posits that age differences in intellectual functioning are largely or completely due to sensory functioning, sensorimotor functioning, and other indicators of bodily function that are generally subsumed under the heading of biomarkers or bioage (Anstey, 1999a; Anstey & Smith, 1999; Heron & Chown, 1967; Stankov & Anstey, 1997). Typically, this hypothesis has been addressed by means of multiple regression or structural equation models, where the direct effect of age on cognition was tested after allowing for its indirect effect specified through the biomarkers. Evidence in favor of the mediation hypothesis would emerge if most variance in intellectual performance were explained for by the biomarkers, but not directly by age. For statistical reasons (Lindenberger & Pötter, 1998), any mediation hypothesis, as a substantive claim, needs to be dissociated from mediation models based on cross-sectional data. The present analyses may offer a viable alternative for the exploration of mediational links. Specifically, a variable may be said to mediate changes in the other if it exerts a direct influence on the change score of the other variables. It may be said to be a strong mediator of change if it influences changes in other variables to a greater extent than its change is influenced by these other variables.

Our analyses revealed that perceptual speed affected change in most other variables, while verbal knowledge was the only variable whose change was affected solely by itself and by chronological age. Both close and distance visual acuity affected the change in only one other variable, while their change was affected by two other variables. Unless perceptual speed is construed as a more valid biomarker than sensory functioning, our evidence does not lend support to a straight-forward longitudinal extension of the biomarker mediation hypothesis. Moreover, there were three reliable effects from cognitive measures to change in sensory variables, while only one from sensory variables to change in cognitive measures. We may hence conclude that the present longitudinal evidence appears to contradict the biomarker mediation hypothesis, which had previously been tested with cross-sectional data.[12]

The common-cause hypothesis of cognitive aging posits that covariations among various brain-related performance measures are indicative of senescent brain changes with widespread intersystemic effects. As a consequence, the covariation between sensory and intellectual aging is taken as an indication of to be identified senescent neural changes affecting both domains (Baltes & Lindenberger, 1997; Lindenberger & Baltes, 1994). The common-cause hypothesis has been addressed by methodologies similar to those used to test the mediation hypothesis, where the variables most frequently examined were again various indicators of sensory, sensorimotor, and intellectual functioning.

As has been noted elsewhere (Baltes & Lindenberger, 1997; Lindenberger & Baltes, 1994), the common-cause hypothesis is, at this point, empirically and theoretically underidentified. Empirically, some of the covariance observed in cross-sectional, age-heterogeneous data, suggestive of the

[12] We thank Keith Widaman for underscoring this result.

operation of a common cause, may have been due to the superimposition of functionally independent but age-linked processes (Lindenberger & Pötter, 1998; Reinert et al., 1966). Theoretically, several candidates for a common cause have been proposed, such as impaired frontal circuitry (Duncan, Emslie, Williams, Johnson, & Freer, 1996), white-matter loss (Sullivan & Pfefferbaum, 2003), grey matter loss (Raz et al., 2005) and deficiencies in dopaminergic neuromodulation (Bäckman & Farde, 2005; for a neurocomputational model, see Li & Lindenberger, 1999; Li, Lindenberger, & Sikström, 2001). The scope and interrelations among these and additional candidate causes remain to be explored. If direct empirical indicators of one or more common causes were available, and if common causes were assumed to influence both age-linked and age-orthogonal aspects of interindividual differences in sensory and intellectual functioning, then such indicators should greatly reduce the amount of static covariance and dynamic effects in the system if its effects were controlled statistically (as was done with chronological age in the present set of analyses). Thus, to empirically specify and disambiguate this hypothesis, future longitudinal and experimental studies should incorporate direct measures of candidate causes (e.g., dopamine receptor density; cf. Bäckman & Farde, 2005; Volkow et al., 2000).

The present results do not exclude the possibility that some portion of the static covariance and dynamic links observed in this data set reflect the operation of a common cause (i.e., of a higher-order, system-general mechanism). However, to a considerable degree, the observed changes were independent of each other and did not adhere to a pattern of unidimensional causality. Clearly, if a common cause exists, it does so in conjunction (and possibly in interaction) with ability-specific processes and mechanisms (for a similar conclusion, see Anstey et al., 2003). At the same time, we cannot exclude that alternative models with more direct indicators of a common cause would further reduce the amount of domain-specific change.

The cascade hypothesis posits that in old age decrements in bodily functions initiate a series of processes leading to a final terminal drop, that is, to precipitous decline in intellectual performance few years prior to death. According to this hypothesis, changes in sensory, sensorimotor, and other indicators of bodily functioning, again construed as biomarkers, as indicators of primary aging, precede and initiate later changes in intelligence. This hypothesis is even more difficult to evaluate with cross-sectional data than the other two as it explicitly specifies a series of time-dependent events (i.e., a cascade). A strict interpretation of the cascade hypothesis appears to be inconsistent with the present findings. There are indeed reliable longitudinal predictions from sensory variables to later intellectual performance, but the opposite is also true. Processes of prediction over time are not exclusively operating from the sensory to the intellectual domain but also in the reverse direction.

This article was not meant to provide a conclusive comparative evaluation of the biomarker mediation, common cause, and cascade hypotheses of cognitive aging. Instead, we wished to promote two intertwined developments, one conceptual and the other methodological, that we see as indispensable means to this end: (a) the formulation of explicit longitudinal and dynamic extensions of each of these three hypotheses; (b) the use of multivariate statistical modeling techniques capturing static and dynamic longitudinal relations. Specifically, we tried to demonstrate that the Dual Change Score Model is a useful methodological tool for advancing and testing hypotheses on the nature of the link between sensory and intellectual domains of functioning. Of course, exploring this sort of hypotheses necessitates not only relatively long term longitudinal data, but also microgenetic time series to test intraindividual within- and between-domain couplings (Lindenberger & Oertzen, in press). At the same time, we recognize that the Dual Change Score Model is not without problems. Prime among these, as common to general structural equation models, is the assumption of incomplete data as missing at random (Rubin, 1974). This assumption justified our estimation procedures based on raw maximum likelihood (Arbuckle, 1996; McArdle, 1994). We contend, though, that rather than basing our findings on the missing at random assumption, we rely on the assumption that the incompleteness mechanisms underlying the overall cognitive–sensory data structure weaken, rather than strengthen, the dynamic relations among variables (Ghisletta & Lindenberger, 2003; Singer et al., 2003). This assumption needs to be investigated in future empirical and simulation work. We ran nevertheless all analyses presented here on the subsample with complete data only ($N = 120$), without finding any substantive difference in results. To the extent that differences between the full sample and the complete-data subsample are predictable from the variables analyzed in our models, the selectivity analyses further supported the reliance on the missing at random assumption.

With the present work we discussed the application of the multivariate Dual Change Score Model as one tool to study predictive links among different domains of functioning. We provided evidence against the automatic merging of indicators that might functionally appear similar, yet obey to different laws when repeatedly observed in time. We systematically analyzed longitudinal changes in intellectual and sensory variables as a dynamic system and explored some hypotheses about longitudinal prediction. In the end, we think we have furthered the efforts to "think longitudinally and dynamically" when investigating well-established links among intellectual, sensory, and sensorimotor domains of functioning, and when formulating hypotheses about the evolution of intelligence across the lifespan (Baltes & Labouvie, 1973; Tetens, 1777). In sum, we believe that times are ripe to further our questions and to ask more of our data.

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