Developmental Psychology
2007, Vol. 43, No. 3, 705–718

0012-1649/07/$12.00 DOI: 10.1037/0012-1649.43.3.705

Well-Being Affects Changes in Perceptual Speed in Advanced Old Age: Longitudinal Evidence for a Dynamic Link

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This study examined competing hypotheses about dynamic cross-domain associations between perceptual speed and well-being in advanced old age. We applied the bivariate dual change score model (J. J. McArdle & F. Hamagami, 2001) to 13-year incomplete longitudinal data from the Berlin Aging Study (P. B. Baltes & K. U. Mayer, 1999; $N = 516$, 70–103 years at T1, $M = 85$ years). Reports of well-being were found to influence subsequent decline in perceptual speed (time lags of 2 years). No evidence was found for a directed effect in the other direction. None of the potential covariates examined (initial health constraints, personality, and social participation) accounted for these differential lead–lag associations. Our results suggest that well-being is not only a consequence of but also a source for successful aging. The discussion focuses on conceptual implications and methodological considerations.

Keywords: oldest old, bivariate dual change score modeling, well-being, cognition, successful aging

Life-span psychological research has long been interested in structural relations among intraindividual changes within and between domains of functioning (Baltes & Nesselroade, 1979; Brandtstädter & Lerner, 1999; Broidy et al., 2003; Dixon, 2005; Hertzog, Dixon, Hultsch, & MacDonald, 2003; Rutter, 1998; Salthouse, 1996; Schulenberg, Bryant, & O'Malley, 2004; Sliwinski, Hofer, & Hall, 2003). The current study explores the dynamic interplay between age-related changes in indicators of two key psychological domains, namely cognition and well-being. Cognitive functioning is viewed as a general-purpose mechanism for adaptation and a resource that people can draw upon in the face of obstacles (Baltes, Lindenberger, & Staudinger, 2006). Well-being is generally considered to be a central component and subjective outcome of successful aging (e.g., Baltes & Baltes, 1990; Lynch & George, 2002; Rowe & Kahn, 1997; Ryff & Singer, 1998). In old age, levels of functioning as well as changes in the two domains are typically weakly to moderately associated (Arbuckle, Gold, & Andres, 1986; Carmelli, Swan, LaRue, & Eslinger, 1997; Gerstorf, Smith, & Baltes, 2006; Isaacowitz & Smith, 2003; Luszcz, 1992; Wetherell, Reynolds, Gatz, & Pedersen, 2002). To account for these associations, unidirectional, bidirectional, and third-variable accounts have been advanced. We empirically compare these different proposals about the dynamic links between certain aspects of cognition and well-being by applying an extension of the latent growth curve model, the bivariate dual change score model (BDCSM; McArdle & Hamagami, 2001) to 13-year incomplete longitudinal data from the Berlin Aging Study (BASE; Baltes & Mayer, 1999).

Starting with a unidirectional perspective, proposals and empirical evidence on potential causal directions between aspects of cognition and well-being are mixed (Albert et al., 1995; Carmelli et al., 1997; Zank & Leipold, 2001). One position argues that cognitive functioning may serve as a general resource that individuals employ to master developmental challenges in a variety of contexts, in turn determining well-being. At an everyday and pragmatic level, low cognitive functioning may act as a risk factor for decline in well-being because it sets constraints on an individual's capacity to manage the routines of everyday life and thereby contributes to reduced satisfaction with life (cf. Maier & Smith, 1999).

Another position argues that well-being, or the absence thereof, may be among the driving forces underlying cognitive change. Specifically, clinical studies have demonstrated that patients diagnosed with depressive disorders (i.e., a reversed indicator of well-being) usually perform poorly on cognitive tasks, particularly those assessing information processing and memory (Bäckman, Hill, & Forsell, 1996; Hart, Kwentus, Hamer, & Taylor, 1987;

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The Berlin Aging Study (BASE) was financially supported by two German federal departments: the Department of Research and Technology (13 TA 011: 1988–1991) and the Department of Family and Senior Citizens (1991–1998). Since 1999, BASE has been funded by the Max Planck Institute for Human Development, where the study is located. Members of the Steering Committee are Paul B. Baltes and Jacqui Smith (psychology), Karl Ulrich Mayer (sociology), Elisabeth Steinhagen-Thiessen and Markus Borchelt (internal medicine and geriatrics), and Hanfried Helmchen and Friedel Reischies (psychiatry). Field research was coordinated at various phases by Reinhard Nuthmann, Karl M. Neher, and Karin Fröhlich.

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Weingartner, 1986). In addition, a growing body of life-span literature suggests that processes of self-evaluation and self-regulation can have fundamental motivational and behavioral consequences (for reviews, see Brandtstädter & Lerner, 1999; Fredrickson, 2001; Lyubomirsky, King, & Diener, 2005). For example, participants with a positive view of their aging process invest more engagement and persistence into doing cognitively demanding tasks, set themselves challenging goals, and are thus better able to exploit their cognitive resources (e.g., Levy, 2003; West, Thorn, & Bagwell, 2003).

Proposals about a bidirectional relationship between cognition and well-being can be found, for example, in the seminal work of M. P. Lawton (1983) who described the two domains as constituting separate, but reciprocally interacting, sectors of the "good life" that both directly and indirectly influence one another (see also Rowe & Kahn, 1997). Finally, it may also be that an underlying third variable or common cause solely accounts for cognition–well-being couplings. Among others, health constraints, personality, and social participation are three candidates for influences shared between the two domains. Each of these factors has been shown to relate to either of the two domains making it possible that such associations may be spurious in the sense that they exclusively reflect a set of shared antecedent conditions.

Both cross-sectional and longitudinal analyses provide evidence that chronic health conditions in old and very old age are not only associated with lower cognitive functioning on measures of perceptual speed and verbal fluency (Verhaeghen, Borchelt, & Smith, 2003) but also limit the potential for well-being (Kunzmann, Little, & Smith, 2000; Mroczek & Spiro, 2005; Smith, Borchelt, Maier, & Jopp, 2002). It is also well established that personality facets such as openness to experience are positively related to performance across a number of psychometric tests of intelligence such as perceptual speed, inductive reasoning, and verbal memory (Arbuckle et al., 1986; Schaie, Willis, & Caskie, 2004). In a similar vein, various personality traits show robust moderate associations to components of well-being (for overview, see Diener & Lucas, 1999; Watson & Clark, 1992). Finally, changes in general measures of an engaged lifestyle such as breadth of leisure activities and engagement in intellectually stimulating activities as well as the quality of one's social environment are associated with changes in aspects of cognitive performance in old age (e.g., Hultsch, Hertzog, Small, & Dixon, 1999; MacKinnon, Christensen, Hofer, Korten, & Jorm, 2003; Seeman, Lusignolo, Albert, & Berkman, 2001). For example, using methods analogous to the one used in this article, Lövdén, Ghisletta, and Lindenberger (2005) found that lower social participation precedes and predicts decline in perceptual speed in old and very old age. Thus, to the extent that social participation is a determinant of well-being (e.g., Antonucci et al., 2002; Menec, 2003), associations among well-being and aspects of cognitive functioning may be spurious.

The accounts reviewed above may all be valid descriptions of dynamic cognition–well-being couplings, depending upon the specific time scale used. Such lead–lag effects may occur over the whole life span, be extended over different phases of life, or restricted to specific phases such as early life. Rather than examining lifetime data (e.g., Gow et al., 2005), the present study asks whether reciprocal and dynamic lead–lag influences between certain aspects of cognitive functioning and well-being exist in old and advanced old age. To do so, we take advantage of a structural equation model, the BDCSM (McArdle & Hamagami, 2001), that has successfully been applied to model dynamic associations within and between domains of functioning (Ferrer & McArdle, 2004; Ghisletta & Lindenberger, 2003; Lövdén et al., 2005; McArdle et al., 2004). The BDCSM combines features of the latent growth curve model (e.g., Bryk & Raudenbush, 1992; Meredith & Tisak, 1990; Raudenbush & Bryk, 2002) and the cross-lagged regressions approach (e.g., Rogosa, 1980). Similar to the family of latent growth curve models, the BDCSM estimates latent intercept and slope factors within a given domain at the population level simultaneously with systematic variance around these means and a separate residual variance term. As an extension of the typical latent growth curve model, the BDCSM additionally allows the estimation of time-lagged relations between states in a given domain and the reliable, error-free portion of subsequent change in the other domain. Unlike typical cross-lagged correlations between variables, the BDCSM allows both adjusting for unequal reliabilities of the variables and separating dynamic changes within variables from lead–lag relations across variables. Thus, with the BDCSM it is possible to compare the substantive hypotheses concerning dynamic relations between aspects of cognitive functioning and well-being in advanced old age.

In this study, we selected perceptual speed as a measure of cognitive functioning because it represents a powerful indicator of cognitive decline in advanced old age and also has excellent psychometric properties (Lindenberger & Baltes, 1997; Verhaeghen & Salthouse, 1997). As a measure of well-being, we used the Philadelphia Geriatric Center Morale Scale (Lawton, 1975), which has a specific aging focus and primarily assesses cognitive–evaluative rather than emotional aspects of well-being, including aging satisfaction and life satisfaction. We applied the BDCSM to 13-year incomplete longitudinal data from 70- to 103-year-old participants in the Berlin Aging Study (Baltes & Mayer, 1999). Specifically, we simultaneously modeled longitudinal changes in perceptual speed and longitudinal changes in well-being and tested hypotheses about the nature of their dynamic interrelationships over time. Testing unidirectional accounts, we asked whether level of perceptual speed leads subsequent 2-year change in well-being or whether it is level of well-being that predicts subsequent change in perceptual speed. We also investigated bidirectional accounts specifying that both lead–lag couplings exist, be they of equal size or not. In addition, we examined the potential role of health constraints, openness to experience, and social participation to test whether such dynamic time-lagged associations are due to one or more underlying additional variables.

Method

The current study uses longitudinal data from six nested subsamples of the interdisciplinary multisession Berlin Aging Study collected over 13 years: at baseline in 1990–1993 (T1; $N = 516$) and in 1993–1994 (T2; $n = 361$), 1995–1996 (T3; $n = 244$), 1997–1998 (T4; $n = 164$), 2000 (T5; $n = 88$), and 2004–2005 (T6; $n = 48$). T2 took place 1.95 years ($SD = 0.71$), T3 3.76 years ($SD = 0.66$), T4 5.53 years ($SD = 0.79$), T5 8.94 years ($SD = 0.84$), and T6 13.00 years ($SD = 0.87$) after T1, respectively. Detailed descriptions of the variables assessed and procedures used, as well as about the longitudinal samples and design, are published in Baltes and Mayer (1999), T. Singer, Verhaeghen, Ghisletta, Lindenberger, and Baltes (2003), and Smith, Maas et al. (2002). A brief overview is given below.

Participants and Procedure

The baseline cross-sectional BASE sample (mean age = 84.92 years, *SD* = 8.66, range: 70–103) was stratified by age and gender with 43 men and 43 women in each of six different age brackets (70–74, 75–79, 80–84, 85–89, 90–94, and 95+ years). To obtain this sample, a total of 1,908 individuals, drawn from the Berlin city registry, were approached for participation. As one would expect given the advanced age of the sample and the high intensity of the assessment procedure, 516 participants of those contacted completed a 14-session intensive assessment protocol. This baseline sample was positively selected on a number of variables (e.g., younger age, lower 1-year mortality as well as better physical health and cognitive functioning, and higher well-being), but the amount of selection bias was relatively small and did not exceed 0.50 *SD* units for any variable considered (for details, see Lindenberger et al. 1999). In addition, the sample was not restricted in heterogeneity and did not exhibit major differences in patterns of covariation among variables (Baltes & Smith, 1997). Since baseline, extensive effort has been invested into maintaining contact with the participants in order to avoid voluntary dropout. As expected, given the mean age of the sample, the primary reason for attrition was mortality. On average, 10% of participants have voluntarily dropped out at each measurement occasion, for the most part because of poor health. At T6, 17% (n = 89) of the initial 516 participants were still alive.

Mean longitudinal selectivity for the measures under consideration was calculated using an effect size metric indicating the degree to which individuals who survived and participated over a 13-year period differed from the parent sample at baseline assessment (for details, see Lindenberger, Singer, & Baltes, 2002; T. Singer et al., 2003). At T6, total selectivity amounted to 0.84 *SD* units (where *SD* refers to that of the parent BASE sample) for perceptual speed, 0.39 *SD* for well-being, −0.99 *SD* for chronological age, 0.59 *SD* for health, 0.44 *SD* for openness to experience, and 0.81 *SD* for social participation. This suggests that younger age and higher levels of functioning at baseline assessment were associated with subsequently lower mortality and higher participation rates among survivors, thereby providing more data points for estimates of change over time. The largest component reflected in sample selectivity was mortality (e.g., 83% for perceptual speed).[1] Implications of nonrandom attrition for the interpretability of the results obtained in this study are considered in the Discussion section.

Trained research assistants and medical personnel carried out all testing in individual face-to-face sessions. With the exception of sessions that involved geriatric medicine, testing took place at the participant's place of residence (i.e., private household or institution). Sessions required an average of 90 min and, when necessary, were split into shorter units of assessment. Over time, the same versions of the tests were administered, and stimulus presentation and data collection for the cognitive measures were supported by a Macintosh SE/30 equipped with a touch-sensitive screen.

Measures

Perceptual speed. The longitudinal cognitive test battery of BASE comprised two tests of perceptual speed: Digit Letter and Identical Pictures.[2] The Digit Letter task closely resembles the well-known Digit Symbol Substitution test of the Wechsler Adult Intelligence Scale (Wechsler, 1982). Throughout the duration of the test (3 min), a template with nine digit-letter pairings was presented to the participants. Participants were shown series of digits (six per page) and were required to name the corresponding letter pair, as fast as possible. In the Identical Pictures task, a target figure and five response alternatives were shown on the computer screen and participants had to touch the correct response figure (which was identical to the target) as quickly as possible. Up to 32 items were presented, and testing terminated automatically after 80 s. The Digit Letter and Identical Pictures tests both showed high reliabilities at T1 (Cronbach's $\alpha > .90$), and the two tests formed a unit-weighted composite of perceptual speed representing the total number of correct responses. Detailed descriptions of the tests and their measurement properties can be found in Lindenberger and Baltes (1997) and Lindenberger, Mayr, and Kliegl (1993). Data for perceptual speed are available for the T1, T3, T4, T5, and T6 measurement occasions in BASE, whereas T2 assessment did not provide comprehensive cognitive data.

Well-being. Factor scores for psychological well-being were derived from a German translation of the 15-item version of the Philadelphia Geriatric Center Morale Scale (Lawton, 1975; for analyses of the factor structure, see Liang & Bollen, 1983), which was specifically designed for use with older adults. The scales used comprised items for three dimensions: nonagitation (6 items), aging satisfaction (5 items), and life satisfaction (4 items). Data for the questionnaire were obtained in tape-recorded interviews with a verbal response format. Participants were asked to indicate how well items described them using a 5-point Likert-scale with 1 labeled as *does not apply to me at all* and 5 labeled as *applies very well to me*. Each item was read aloud by the research assistants. Detailed descriptions of the tests and their measurement properties can be found in Smith, Fleeson, Geiselmann, Settersten, and Kunzmann (1999). Data for well-being are available from all six measurement occasions in BASE.

Covariates. The measure for health constraints was the number of physician-observed diagnoses of moderate to severe chronic illnesses, according to the International Classification of Diseases–9 (for details, see Steinhagen-Thiessen & Borchelt, 1999). The diagnoses were determined in clinical examinations and supported by additional blood and saliva laboratory assessments. To assess openness to experiences, we selected items from the Neuroticism–Extroversion–Openness Inventory (Costa & McCrae, 1985; for details, see Smith & Baltes, 1999). Specifically, the measure was derived from responses to six items assessing the facets of fantasy, ideas, feelings, aesthetics, and actions (e.g., "I

[1] Mortality information was missing for n = 22 because they had moved out of the Berlin area.

[2] In the cross-sectional analysis at T1 as reported by Lindenberger and Baltes (1997), perceptual speed was measured by three tests. Due to time restrictions at follow-up occasions, only two tests of perceptual speed were administered: Digit Letter and Identical Pictures.

often try new things”). The measure of social participation represented a unit-weighted composite of social activities as mentioned in the Yesterday Interview and the number of social activities mentioned in an Activity List (for details, see Lövdén et al., 2005). From the semistructured Yesterday Interview of all activities a given participant engaged in during the day preceding the interview (Moss & Lawton, 1982), we used the total time (minutes) spent being engaged in leisure activities (e.g., attending cultural events), instrumental activities beyond personal care (e.g., banking), social activities (e.g., visiting people), and work (e.g., regular paid work). For the Activity List (Mayer, Maas, & Wagner, 1999), participants were shown cards each illustrating a category of activities and were asked whether they had engaged in activities of that kind during the last 12 months. The categories were sports, restaurant visits, dancing, day trips, attending cultural events, hobbies, volunteer work, traveling, creative activities, playing games, continuing education, and political activities. We used the number of categories of activities in which participants reported at least one activity.

Data Preparation

As in most previous publications from BASE, measures were standardized to the T metric ($M = 50$, $SD = 10$), with the parent (T1) BASE sample ($N = 516$) providing the reference. This transformation ensured a common metric across variables, while maintaining the psychometric properties of the scores and the longitudinal changes in means and variances.

For the perceptual speed measure, missing data not related to attrition amounted to 9% (88 of 982 attainable data points over the five assessments) and was primarily due to poor vision making computerized testing of performance totally or partly impossible. In line with earlier longitudinal reports of BASE (e.g., Lövdén et al., 2005; T. Singer et al., 2003), no data imputation procedure was applied. The average longitudinal observation intervals were 2.98 years ($SD = 4.20$; range = 0–15 years) for perceptual speed and 3.73 years ($SD = 3.99$; range = 0–15 years) for well-being.

Table 1 presents the age at assessment as well as means and standard deviations for the variables under study. This table illustrates that participants were tested, on average, in their mid- to late 80s. As is also evident, the means for perceptual speed increase because of longitudinal attrition, but the magnitude of between-person differences in both variables is not differentially affected. Implications of nonrandom attrition for the interpretability of the results obtained in this study are considered in the Discussion section.

Statistical Procedures

A graphical representation of the BDCSM as applied in this study is given in Figure 1. The diagram shows observed (manifest) variables as squares, unobserved (latent) variables as circles, and the required constant as a triangle, as well as fixed model parameters as one-headed arrows and random parameters as two-headed arrows. Unlabeled paths are fixed to 1. The separately estimated error terms (e_x, e_y) are assumed to be normally distributed with a mean of zero and a time-invariant variance and to be uncorrelated with all other components. The observed variables x_1, x_3, x_4, x_6, and x_8 represent the five assessments of perceptual speed, whereas

Table 1
Age at Assessment and Descriptive Statistics for Measures Entered Into the Bivariate Dual Change Score Model

Measure and occasion	*n*	Age	*M*	*SD*
Perceptual speed				
T1	466	84.14	50.51	10.16
T3	190	83.27	54.45	9.54
T4	124	83.34	55.45	9.42
T5	73	85.48	57.71	8.74
T6	41	88.76	53.32	8.25
Well-being				
T1	516	84.92	50.00	10.00
T2	361	85.26	48.04	10.15
T3	244	84.34	47.94	10.17
T4	164	84.07	46.42	9.97
T5	88	85.87	47.87	10.87
T6	48	89.36	48.41	8.03
Health constraints				
T1	516	84.92	50.00	10.00
Openness				
T1	516	84.92	50.00	10.00
Social participation				
T1	516	84.92	50.00	10.00

Note. *T*-scores standardized to cross-sectional Berlin Aging Study sample ($N = 516$; $M = 50$, $SD = 10$).

the observed variables y_1, y_2, y_3, y_4, y_6, and y_8 represent the six assessments of well-being. In contrast, the variables x_2, x_5, and x_7, and y_5 and y_7 are unmeasured “node” variables added to account for occasions on which a given variable was not assessed, which assures an equal-interval approach of approximately 2 years in between occasion (see also Table 1). This equal-interval approach simplifies the estimation and interpretation of model parameters, and guarantees time-invariant scaling of all parameters. The scores $x[t]$ (or $y[t]$) are defined as the unit-weighted sum of the latent score at $x[t - 1]$ (or $y[t - 1]$) plus the latent difference score $\Delta x[t]$ (or $\Delta y[t]$) so that the latent difference scores represent the latent, reliable, change score between $x[t - 1]$ and $x[t]$ (or $y[t - 1]$ and $y[t]$; McArdle & Nesselroade, 1994). The intercept X_0 and Y_0 (i.e., an individual’s score at T1) and slope factors X_S and Y_S (i.e., an individual’s linear 2-year change scores) are supposed to account for the time series information of both variables x and y; intercepts and slopes are estimated at the population level (μ_{x0}, μ_{xS}; μ_{y0}, μ_{yS}), and they are allowed to vary (σ_{x0}, σ_{xS}; σ_{y0}, σ_{yS}) and to covary (ρ_{x0xS}, ρ_{y0yS}, ρ_{x0y0}, ρ_{xSyS}, ρ_{x0yS}, ρ_{y0xS}).

The slope factors X_S and Y_S represent linear change because they relate to the latent difference scores $\Delta x[t]$ and $\Delta y[t]$ with a constant loading of 1. As an extension of typical linear latent growth curve models, the difference scores $\Delta x[t]$ and $\Delta y[t]$ are defined as the unit-weighted sum of the linear component of change within a given variable plus two additional influences. The first addition is an auto-proportion parameter β_x (or β_y) that denotes the effect of variable x (or y) at time t – 1 on subsequent change in variable x (or y) between times t – 1 and t. This effect represents the effect that level of functioning on one variable has on subsequent change of this variable. Second, an intervariable cross-lagged parameter γ_{xy} (or γ_{yx}) is estimated that represents the effect of variable x (or y) at time t – 1 on subsequent change in the other variable y (or x) between times t – 1 and t. For reasons of

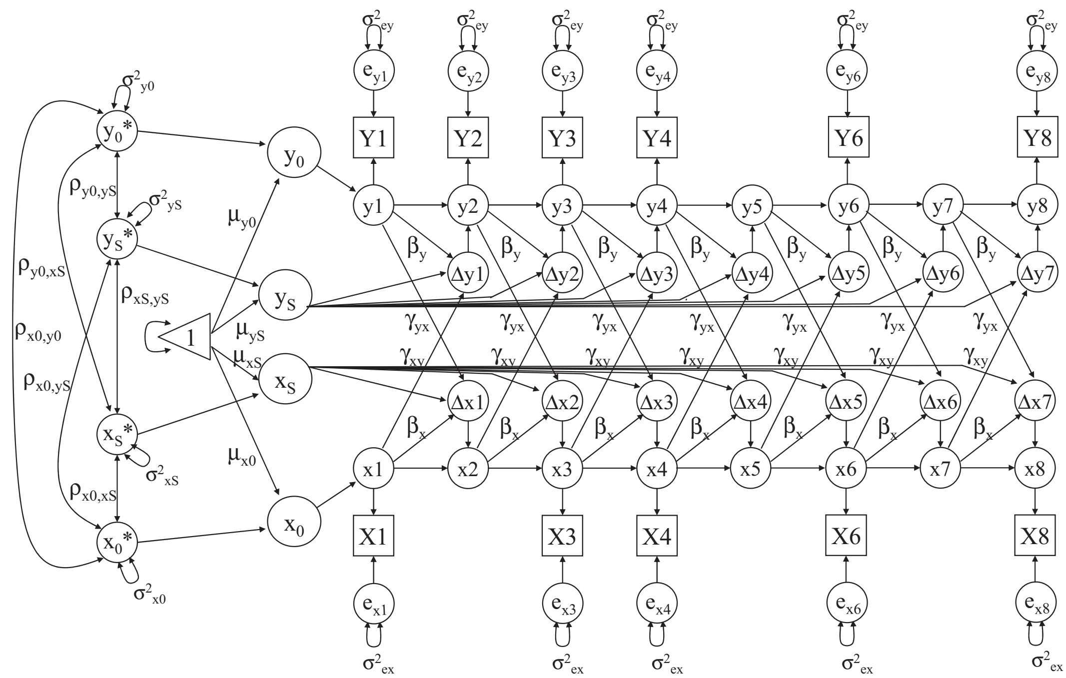

Figure 1. Graphical representation of the bivariate dual change score model (McArdle & Hamagami, 2001) as applied in the current study. Observed variables are represented by squares, latent variables by circles, regression weights by one-headed arrows, and variances and covariances by two-headed arrows. The triangle represents a constant indicating means and intercepts. All unlabeled paths are set to 1.

simplicity and model identification, both β and γ parameters are often set to be equal across time, although this in principle is a testable assumption. With β and γ parameters set to zero, the BDCSM is equivalent to a (bivariate) linear latent growth curve model. A more detailed description of the BDCSM and its assumptions is published in recent work from McArdle and colleagues (Ferrer & McArdle, 2004; McArdle & Hamagami, 2001; McArdle et al., 2004) and others (Ghisletta & de Ribaupierre, 2005; Ghisletta & Lindenberger, 2003, 2005; Lövdén et al., 2005).

The major empirical interest of this study is in the interdomain, cross-lagged γ or coupling parameters. Specifically, implementing the BDCSM allows for a direct empirical comparison of competing substantive hypotheses about the dynamic effects of state of perceptual speed on subsequent change in well-being ($\gamma_{\text{SPEED–WB}}$), and conversely, of state of well-being on subsequent change in perceptual speed ($\gamma_{\text{WB–SPEED}}$). In contrast to the static intercept–intercept and slope–slope correlation, inspection of these dynamic cross-lagged γ parameters may inform us about lead–lag patterns in the data. Because of the 30-year age range of our sample, all analyses included age as a time-invariant covariate that influenced the latent intercept factors as well as the latent difference scores (with an equal effect over time), thereby residualizing all model parameters for chronological age.[3] Most importantly, the coupling parameters reported are thus statistically adjusted for the nonlinear change component of the auto-proportion parameters as well as for chronological age.

We used Amos 5.0 for all analyses and employed the full-information maximum likelihood (FIML) estimation algorithm to all data points available to accommodate incomplete data (i.e., no participants were excluded; see Table 1). That is, all obtained observations for all participants on all measurement occasions are used to build up maximum-likelihood estimates using a numerical routine that optimizes the model parameters with respect to any available data (cf. McArdle et al., 2004). This also allows adjusting for unbalanced data structures (J. D. Singer, 1998) and longitudinal selectivity under the assumption that data are missing at random (MAR; i.e., prior differences in level and observed change predict subsequent participation; McArdle, 1994), particularly when attrition-informative variables such as age are included as well (for a nontechnical treatment, see Schafer & Graham, 2002). Chronological age was centered at the mean age of the total T1 BASE sample, resulting in intercept means, intercept variances, and slope-intercept covariances being estimated at age 85 years.

Results

Our findings are organized in three sections. First, we report results from the comparison of models attempting to operationally define the above unidirectional, bidirectional, and third-variable accounts of perceptual speed–well-being couplings through different model specifications of the lead–lag and coupling parameters. In a second step, we aim at illustrating the differential magnitude

[3] This model estimated 26 parameters, namely two times seven parameters within each of the two time series (μ_0, μ_S, σ_0, σ_S, ρ_{0S}, β, e), plus four intercorrelations (ρ_{0x0y}, ρ_{SxSy}, ρ_{0xSy}, ρ_{0y0x}) and two coupling between the time series (γ_x, γ_y), as well as the six parameters for age (μ_{Age}, σ_{Age}, Age_{0x}, Age_{0y}, Age_{Sx}, Age_{Sy}).

of the coupling parameters found by focusing on both the best-fitting model and the model postulating that both perceptual speed and well-being are dynamically active in the system. In a final set of analyses, we explore whether controlling for initial (i.e., T1) health constraints, openness to experience, and social participation had an effect on the dynamic associations between perceptual speed and well-being.

Comparison of Various Models of Perceptual Speed–Well-Being Couplings

To directly test the opposing hypotheses of perceptual speed–well-being couplings, we compare the goodness-of-fit indices of five statistically nested models. Specifically, a model that freely estimated both cross-lagged coupling parameters $\gamma_{SPEED-WB}$ and $\gamma_{WB-SPEED}$ was referred to as the full coupling model; this model was the least parsimonious of the models estimated and thus served as a reference. The other four estimated models are nested under the full coupling model. In a second model, coupling $\gamma_{SPEED-WB} = 0$, the coupling from perceptual speed on change in well-being was set to zero, whereas the coupling from well-being to change in perceptual speed was freely estimated. If this model were found to reveal a significant loss in goodness-of-fit statistics as compared with the full coupling model, then we cannot reject the unidirectional account that perceptual speed leads change in well-being. In our third model, coupling $\gamma_{WB-SPEED} = 0$, the coupling from well-being on change in perceptual speed was fixed at zero, whereas the coupling from perceptual speed on change in well-being was estimated. If this model were found to show a similarly good fit to the data as compared with the less parsimonious full coupling model, then we can reject the unidirectional hypothesis that well-being leads change in perceptual speed. The fourth model specified, equal coupling, represents one operational definition of a bidirectional account in that both coupling parameters $\gamma_{SPEED-WB}$ and $\gamma_{WB-SPEED}$ are estimated and set to be of equal size. The fifth model, no coupling, specifies that neither of the two coupling parameters exists by setting both $\gamma_{SPEED-WB}$ and $\gamma_{WB-SPEED}$ at zero. If Model 4 or Model 5 were to provide a worse description of the data as compared with the full coupling model, then the hypothesis cannot be rejected that the coupling parameters are of unequal size or that dynamic coupling exists between perceptual speed and well-being, respectively.

The upper rows in Table 2 contain various goodness-of-fit indices used to compare the age-adjusted models. (Comparison of models adjusted for age, health constraints, openness, and social participation are also included and are discussed later.) The difference in χ^2 statistics in the third column, for example, indicates that not allowing for a lagged influence from perceptual speed onto changes in well-being (coupling $\gamma_{SPEED-WB} = 0$) was associated with a negligible loss in fit, $\Delta\chi^2 = 1.43$, $df = 1$, $p > .10$, whereas not allowing for a lagged influence from well-being onto changes in perceptual speed (coupling $\gamma_{WB-SPEED} = 0$) resulted in a highly significant loss in fit relative to the full coupling model, $\Delta\chi^2 = 13.66$, $df = 1$, $p < .001$. In addition, the equal coupling model, $\Delta\chi^2 = 9.85$, $df = 1$, $p < .001$, and the no coupling model, $\Delta\chi^2 =$

Table 2
Goodness-of-Fit Model Comparison Among Alternative Bivariate Models of Perceptual Speed (SPEED) and Well-Being (WB), Using the 13-Year Berlin Aging Study Sample, Including Age as a Covariate, With and Without Additionally Including Health Constraints, Openness to Experience, and Social Participation

Model	Goodness-of-fit indices					
	χ^2 (*df*)	$\Delta\chi^2$ (*df*)	CRMSEA	RMSEA	BCC	CFI
Age included						
Unidirectional						
Coupling $\gamma_{SPEED\text{-}WB} = 0$	112.28 (65)	1.43 (1)	.029	.038	163.57	.966
Coupling $\gamma_{WB\text{-}SPEED} = 0$	124.51 (65)	13.66 (1)***	.157	.042	175.80	.958
Bidirectional						
Equal coupling	120.70 (65)	9.85 (1)***	.123	.041	171.99	.960
Full coupling	110.85 (64)	—	—	.038	164.20	.967
No coupling	128.54 (66)	17.69 (2)***	.131	.043	177.79	.955
Age, health constraints, openness, and social participation included						
Unidirectional						
Coupling $\gamma_{SPEED\text{-}WB} = 0$	139.97 (86)	1.24 (1)	.022	.035	241.11	.971
Coupling $\gamma_{WB\text{-}SPEED} = 0$	157.64 (86)	18.91 (1)***	.186	.040	258.77	.961
Bidirectional						
Equal coupling	158.17 (86)	19.44 (1)***	.189	.040	259.31	.961
Full coupling	138.73 (85)	—	—	.035	241.93	.971
No coupling	160.47 (87)	21.74 (2)***	.138	.040	259.55	.961

Note. Significance refers to loss in χ^2 assuming the full coupling model to be correct. CRMSEA = comparative root mean square error of approximation; RMSEA = root mean square error of approximation; BCC = Browne-Cudeck criterion; CFI = comparative fix index.
*** $p < .001$.

17.69, $df = 2$, $p < .001$, both described the structure of the data less precisely than the full coupling model, suggesting that we can accept neither of the two models. All other fit indices in Table 2 provide a similar pattern of results. Specifically, the comparative root mean square error of approximation (CRMSEA; which relates the difference in the χ^2 value to sample size and model parsimony; Browne & DuToit, 1992) was below .05 for the coupling $\gamma_{\text{SPEED–WB}} = 0$ model, indicating almost no statistical difference to the full coupling model, whereas values for all other models were well above the critical 0.05. The root mean square error of approximation, the Browne-Cudeck criterion, and the comparative fit index also show similar goodness-of-fit values for the coupling $\gamma_{\text{SPEED–WB}} = 0$ model and the full coupling model and less of a fit for the three other models. In sum, nested model comparisons revealed that 13-year longitudinal BASE data during advanced old age do not allow us to reject the hypothesis that well-being leads change in perceptual speed, but hypotheses proposing a leading role of perceptual speed for change in well-being, an equal size of the coupling parameters, and the nonexistence of these coupling parameters could be rejected.

Illustration of the Differential Magnitude of Perceptual Speed–Well-Being Couplings

To illustrate the differential magnitude of the cross-lagged effects $\gamma_{\text{SPEED−WB}}$ and $\gamma_{\text{WB−SPEED}}$, we first show how these coupling parameters are embedded in other components of change. In a second step, we demonstrate how the change trajectories on a given dimension are differentially affected by the coupling parameter of the other dimension.

Figure 2 provides a graphical example of the conjoint product of the various components of change modeled by the BDCSM (i.e., linear change, auto-proportion parameter, coupling parameter, and the effect of age). Specifically, the figure shows the model-implied mean longitudinal trajectories from the full coupling model for perceptual speed and well-being, as produced by the formulas $x[t] = 1 \times X_S + (1 + \beta_x) \times x[t-1] + \gamma_{yx} \times y[t-1]$ and $y[t] = 1 \times Y_S + (1 + \beta_y) \times y[t-1] + \gamma_{xy} \times x[t-1]$ when applied for a person of age 85 years. For $x[1]$ and $y[1]$, the mean equals x_0 and y_0, respectively. What can be seen from Figure 2 is that both perceptual speed (> 15 *T*-score units) and well-being (> 5 *T*-score units) declined substantively in the overall sample over the 13-year period. This model-implied decline over time is in sharp contrast to the attrition-based increase in the observed means for perceptual speed and the rather divergent pattern for well-being as displayed in Table 1. Such a discrepancy illustrates that the model produces estimates of average within-person change in the overall sample whether or not an individual stayed in the sample over time (i.e., MAR assumption).

To better understand the differential magnitude of the coupling parameters and their effects over time, we varied the initial sample means for one variable by half a standard deviation (i.e., 5 *T*-score units from 40 to 60) while keeping the initial sample means for the other variable constant. Specifically, the left-hand panel of Figure 3 shows model-implied change over 13 years (at an average age value of 85 years) in the hypothetical case that all participants showed similar performance on the perceptual speed measure at T1 but differed in their initial levels of well-being. As is evident from this model-implied change as a function of well-being, the change trajectories over time considerably differ from one another in that participants with high initial levels of well-being showed relatively shallower cognitive decline, whereas low initial well-being resulted in steeper cognitive decline. Conversely, the right-hand panel of Figure 3 shows model-implied change as a function of perceptual speed in that we have varied the initial sample means

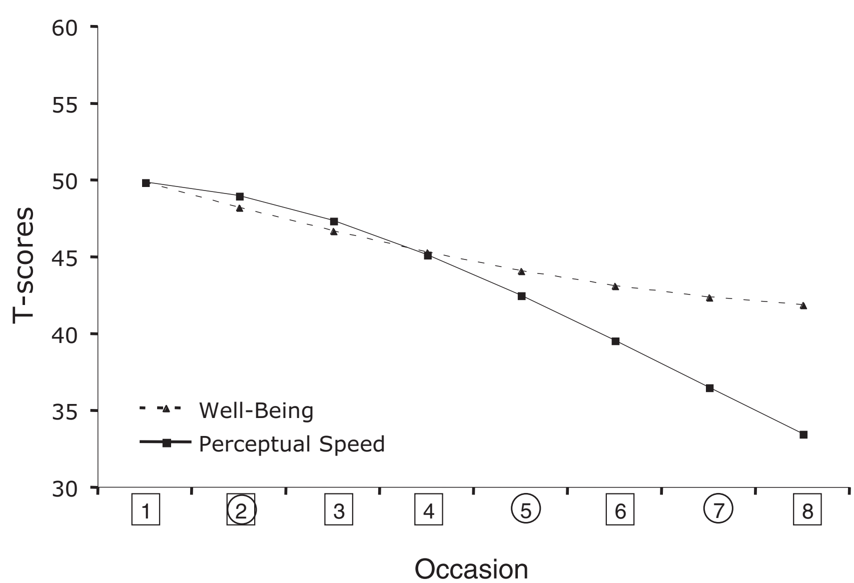

Figure 2. Model-implied mean longitudinal change trajectories over time for perceptual speed (solid line) and well-being (dashed line), as revealed from the bivariate dual change score model (full coupling) for a person of sample average age (85 years). On the *x*-axis, observed variables are represented by squares and latent variables are represented by circles.

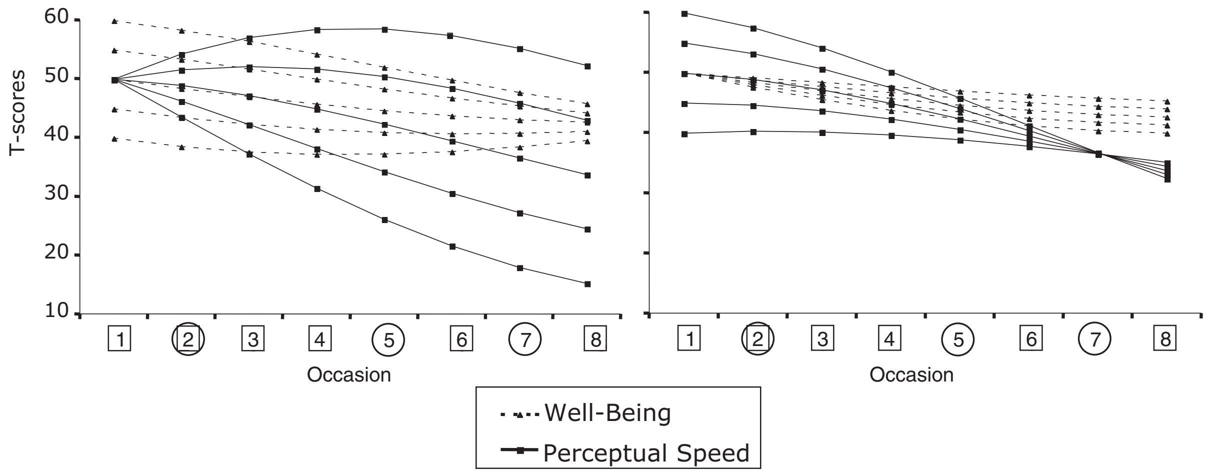

Figure 3. Graphical illustration of the differential magnitude of the coupling parameters and their effects over time. Model-implied sample means from the bivariate dual change score model (full coupling) for the hypothetical case that the initial sample means for one variable (left panel: well-being; right panel: perceptual speed) were varied by half a standard deviation (i.e., 5 *T*-score units from 40 to 60), while the initial sample means for the other variable were kept constant (left panel: perceptual speed; right panel: well-being). For example, the thick lines in the left panel show that, under the assumption of comparable perceptual speed performance at T1, participants with reports of high initial well-being showed relatively shallow cognitive decline, whereas those who reported less well-being initially showed relatively steep cognitive decline. In contrast, the thick lines in the right panel show that well-being trajectories over time are minimally changed as a function of different levels of perceptual speed at T1. On the *x*-axis, observed variables are represented by squares and latent variables are represented by circles.

for perceptual speed by 5 *T*-score units but kept constant the initial level for well-being. In contrast to the spreading-out effect shown in the left-hand panel, model-implied change as a function of perceptual speed resulted in rather minor differences in change trajectories for well-being. Nominally, the coupling parameter $\gamma_{\mathrm{WB-SPEED}}$ was positive and statistically significant (0.53, SE = 0.12, $p < .001$), whereas the coupling parameter $\gamma_{\mathrm{SPEED-WB}}$ was slightly negative and not statistically different from zero (–0.08, $SE = 0.04$, $p > .10$).

The Role of Health Constraints, Openness, and Social Participation

In a final set of analyses, we explored whether individual differences in three neighboring functional domains—health constraints, openness, and social participation—may account for the dynamic couplings between well-being and perceptual speed. To do so, we added indicators representing these domains as time-invariant covariates of the latent intercept factors and the latent difference scores. In these analyses, the coupling parameters (and all other model parameters) are thus residualized for age as well as for first-occasion individual differences in each of these covariates.

Most importantly, controlling for health constraints, openness, and social participation did not substantially alter the dynamic structure reported above. As the lower rows of Table 2 indicate, the coupling $\gamma_{\mathrm{SPEED-WB}} = 0$ model provides the least parsimonious description of the structure in the data, $\Delta\chi^2 = 1.24$, $df = 1$, $p > .10$, whereas all other models are statistically rejected as compared with the full coupling model (coupling $\gamma_{\mathrm{WB-SPEED}} = 0$: $\Delta\chi^2 = 18.91$, $df = 1$, $p < .001$; equal coupling: $\Delta\chi^2 = 19.44$, $df = 1$, $p < .001$; no coupling: $\Delta\chi^2 = 21.74$, $df = 2$, $p < .001$). Parameter estimates and their standard errors from the full coupling model including age, health constraints, openness, and social participation as time-invariant covariates are presented in Tables 3 and 4.

Specifically, Table 3 shows that perceptual speed displayed linear decline ($\mu_{xS} = -19.79$, $p < .001$) as well as an acceleration of decline over time ($\beta_x = -0.17$, $p < .01$), whereas both decline parameters were not different from zero for well-being ($\mu_{yS} = 2.50$, $p > .10$; $\beta_y = -0.01$, $p > .10$), after adjusting for age, health constraints, openness, and social participation. In addition, variance parameters for the intercept and slope factors were statistically significant, suggesting reliable interindividual differences in initial levels and changes over time on perceptual speed and well-being. Finally, inspection of parameter estimates for the effect of covariates on the intercept and slope factors indicate that (a) older participants performed lower on the perceptual speed tasks and showed steeper decline on perceptual speed as well as well-being, (b) health constraints relate negatively to well-being both in terms of mean levels and change over time but do not relate to perceptual speed, (c) openness to new experiences shows strong associations to performance on perceptual speed tasks but not to cognitive decline nor status and change in well-being, and (d) more initial social participation is related to better cognitive performance and higher well-being but not to differential change. Inclusion of these covariates also contributed significant proportions of overall explained variance to the model parameters (e.g., perceptual speed μ_{x0}: $R^2 = .56$ vs. $R^2 = .41$ with and without the three covariates).

Table 3
Results From a Bivariate Dual Change Score Model (Full Coupling) for Perceptual Speed and Well-Being, Using the 13-Year Berlin Aging Study (BASE) Sample: Parameter Estimates for Age, Health Constraints, Openness to Experience, and Social Participation on Perceptual Speed and Well-Being

	Perceptual speed		Well-being	
Parameter	Estimate	*SE*	Estimate	*SE*
Initial mean μ_0	49.60***	0.32	49.86***	0.34
Slope mean μ_S	−19.79***	3.43	2.50	1.16
Proportion β	−0.17**	0.06	−0.01	0.02
Initial variance σ^2_0	34.46***	3.38	43.40***	3.48
Slope variance σ^2_S	17.03*	7.28	0.48*	0.20
Error variance σ^2_e	14.26***	1.34	18.31***	0.92
Age	−0.38***	0.05	0.00	0.05
Age × Slope	−0.16***	0.04	−0.10***	0.02
Health constraints	−0.52	0.33	−1.51***	0.34
Health Constraints × Slope	0.58	0.31	−0.20*	0.10
Openness	1.48***	0.34	0.18	0.35
Openness × Slope	0.40	0.29	0.11	0.12
Social participation	4.58***	0.40	1.13**	0.41
Social Participation × Slope	0.05	0.37	0.30	0.19

Note. Perceptual speed and well-being were *T*-standardized to the cross-sectional BASE sample ($N = 516$; $M = 50$, $SD = 10$). Age was centered at zero, and health constraints, openness, and social participation were *z*-standardized. All estimates are unstandardized.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Consistent with the above results for the age-adjusted models, Table 4 shows that the cross-lagged effect $\gamma_{\text{SPEED–WB}}$ was not statistically significant (–0.07, $SE = 0.04$, $p > .10$), but the coupling from well-being on change in perceptual speed, $\gamma_{\text{WB–SPEED}}$, was positive and statistically significant (0.55, $SE = 0.12$, $p < .001$). Table 4 also presents means and variances for the covariates as well as the intercorrelations among both the covariates and the intercept and slope factors. For example, the correlation between performance in perceptual speed and status on well-being was nonsignificant ($\rho_{\text{SPEED}_0,\text{WB}_0} = .11$, $p > .10$), providing another rationale for heuristically varying one variable, while keeping constant the other (as done in Figure 3).

Although the overall pattern of parameter estimates was within admissible ranges, we would like to highlight a concern. Specifically, model parameters such as coupling effects or correlations should not be interpreted in isolation but only in concert with the other model parameters that were simultaneously estimated (e.g., β). To emphasize this concern, we opted for plotting the model-implied means (see Figures 2 and 3), which represent the dynamic systems equations as a whole. In this vein, we would like to highlight that correlations (e.g., $\rho_{\text{WB}_0,\text{SPEED}_S} = –.85$) are part of complex dynamic expectations and must not be interpreted in isolation (cf. Lövdén et al., 2005).

Discussion

The central objective of this study was to examine dynamic cross-domain associations between perceptual speed and well-being in advanced old age. Specifically, we asked whether the influence of level of perceptual speed on subsequent change in well-being is different in magnitude from the influence of level of well-being on change in perceptual speed. To do so, we applied a bivariate extension of the Dual Change Score Model (McArdle & Hamagami, 2001) to 13-year incomplete longitudinal data from 70- to 103-year-old participants in the Berlin Aging Study (Baltes & Mayer, 1999; $N = 516$).

At the sample level, both perceptual speed and well-being declined over time and between-person variability in these longitudinal changes was dynamically linked. Our results clearly indicate evidence for a unidirectional account of the coupling of decline. Specifically, higher levels of well-being precede and predict 2-year positive deviations from linear decline in perceptual speed (i.e., reduced decline). There was no evidence for the opposite unidirectional pattern or a bidirectional association. The lack of evidence for proposals that (decline in) perceptual speed precedes change in well-being is consistent with evidence from Deary and colleagues who reported that lifetime changes (11–79 years, on average) in cognitive functioning was not associated with satisfaction with life in old age (Gow et al., 2005). Inclusion of covariates from related domains revealed that none of the three candidates examined (health constraints, personality, and social participation) accounted for these differential lead–lag couplings.

Table 4
Parameter Estimates From a Bivariate Dual Change Score Model (Full Coupling) of Perceptual Speed (SPEED) and Well-Being (WB), Using the 13-Year Berlin Aging Study Sample: Covariances Between Level and Change in Perceptual Speed and Well-Being and Age, Health Constraints, Openness to Experience, and Social Participation

Parameter	Estimate	*SE*
Coupling $\gamma_{\text{SPEED-WB}}$	−0.07	0.04
Coupling $\gamma_{\text{WB-SPEED}}$	0.55***	0.12
Mean age μ_{AGE}	0.00[a]	0.38
Mean health constraints μ_{HEALTH}	0.00[b]	0.04
Mean openness μ_{OPENNESS}	0.00[b]	0.04
Mean participation $\mu_{\text{PARTICIPATION}}$	0.00[b]	0.04
Variance age σ^2_{AGE}	75.11***	4.68
Variance health constraints σ^2_{HEALTH}	1.00[b]***	0.06
Variance openness $\sigma^2_{\text{OPENNESS}}$	1.00[b]***	0.06
Variance participation $\sigma^2_{\text{PARTICIPATION}}$	1.00[b]***	0.06
Correlation $\rho_{\text{AGE, HEALTH}}$	.24***	
Correlation $\rho_{\text{AGE, OPENNESS}}$	−.20***	
Correlation $\rho_{\text{AGE, PARTICIPATION}}$	−.55***	
Correlation $\rho_{\text{HEALTH, OPENNESS}}$	−.10*	
Correlation $\rho_{\text{HEALTH, PARTICIPATION}}$	−.23***	
Correlation $\rho_{\text{OPENNESS, PARTICIPATION}}$	.32***	
Correlation $\rho_{\text{SPEED}_0,\text{ SPEED}_S}$	.24*	
Correlation $\rho_{\text{WB}_0,\text{ WB}_S}$	.15	
Correlation $\rho_{\text{SPEED}_0,\text{ WB}_S}$	.42	
Correlation $\rho_{\text{WB}_0,\text{ SPEED}_S}$	−.85***	
Correlation $\rho_{\text{SPEED}_0,\text{ WB}_0}$	.11	
Correlation $\rho_{\text{SPEED}_S,\text{ WB}_S}$	−.02	

Note. All estimates, except correlations, are unstandardized. The significance tests assigned to the correlations refer to the corresponding covariances. Zero subscript indicates initial; S subscript indicates slope.
[a] Age was centered at zero. [b] Health constraints, openness, and social participation were *z*-standardized.
* $p < .05$. *** $p < .001$.

Conceptual Implications

Our results add to the growing body of research showing that aspects of well-being cannot only be considered an outcome of successful aging but also represent a valid predictor of successful aging outcomes over time (for emotional aspects of well-being, see Lyubomirsky et al., 2005). Despite a general self-enhancement bias in well-being (e.g., the stability-despite-loss paradox), perceptions and evaluations of the self show sufficient reliable diversity allowing subtle differences to be powerful enough to predict outcomes such as morbidity (Levy, 2003) and mortality (Danner, Snowdon, & Friesen, 2001; Maier & Smith, 1999).

To avoid a possible misunderstanding of our findings, it is important to note that we certainly do not contend that well-being constitutes a major source of cognitive decline. It is well-known that age-normative cumulative decline in performance on tasks of perceptual speed commences in early adulthood (e.g., Salthouse, 2004). The shape of the age-graded trajectory for well-being, in contrast, is characterized primarily by long-term stability at least into young old age (Diener, Suh, Lucas, & Smith, 1999). Nevertheless, our results indicate that well-being might be a factor that moderates (e.g., slows the pace of) decline in indicators of cognitive functioning during old and very old age. In line with this general interpretation, we found a substantively identical pattern of results when we considered a different measure of cognitive ability, namely verbal fluency (i.e., Categories and Word Beginnings tests), which is less age-sensitive than perceptual speed.

Conceptually, it is an open question as to what extent well-being directly or indirectly relates to maintenance and change in aspects of cognitive functioning over the life span and especially in old age. Preserved well-being could have profound motivational and behavioral consequences (e.g., engagement and persistence) that may in the long run either restrain or help to exploit an individual's cognitive resources (Furry & Baltes, 1973; Levy, 2003). From another perspective, several authors have pointed to the physiological effects of positive or negative self-perceptions of one's life and aging with regard to cardiovascular activity and recovery after heart attack (Danner et al., 2001; see also Kiecolt-Glaser, McGuire, Robles, & Glaser, 2002; Steptoe, Wardle, & Marmot, 2005). Such physiological effects could also influence the brain and thus have an impact on level and change in cognitive performance. A third line of reasoning posits that well-being ratings represent evaluations that might reflect quite accurate summary perceptions of an individual's functioning in a variety of domains as well as age-related changes in these domains (e.g., temporal within-person comparisons; cf. Maier & Smith, 1999). Negative evaluations themselves may thus not be the direct cause for an increased risk for cognitive decline, but instead reflect potential causes from other domains of functioning (e.g., health or biological functioning).

In an attempt to explore such third-variable accounts for time-lagged associations between perceptual speed and well-being, we examined the role of three candidate factors known to relate to either of the two domains (e.g., Bauer & McAdams, 2004; Hultsch et al., 1999; Kunzmann et al., 2000; Lövdén et al., 2005; Mroczek & Spiro, 2005; Schaie et al., 2004; Seeman et al., 2001; Verhaeghen et al., 2003; Watson & Clark, 1992). We found no evidence that individual differences in health constraints, personality, or social participation at the first occasion may account for the observed pattern of differential lead–lag associations between perceptual speed and well-being. We also explored which end of the functional spectrum (negative vs. positive) may drive the dynamic aspects of the perceptual speed–well-being link. To do so, follow-up analyses included clinical diagnoses of dementia and depression (for details, see Helmchen et al., 1999) as well as life-history status at baseline assessment (for details, see Mayer et al., 1999) as time-invariant covariates into our models. The substantive pattern of results found remained unchanged, suggesting that the differential magnitude of the coupling parameters is neither merely a function of criterion-relevant pathology nor of disadvantageous life circumstances.

Despite statistical control of dementia and depression at first occasion, the present data did not allow us to decide whether preserved well-being serves as a protective factor against decline in perceptual speed, whether reduced well-being may act as a risk factor for cognitive decline, or whether both mechanisms are operating at the same time. For example, stress and associated low well-being may relate to negative brain changes (Gould, Tanapet, McEwen, Flugge, & Fuchs, 1998) and thereby link to declining performance on some cognitive tests in old age (Wilson, Mendes de Leon, Bennett, Bienias, & Evans, 2004). Another scenario might be that different trends for lead–lag relations emerge when resources in a given domain are taxed or when other operational definitions for one of the domains are considered (e.g., emotion-based aspects of well-being; Diener & Lucas, 2000; Watson, Clark, & Tellegen, 1988). Given the scarcity of research on associations between aspects of cognition and well-being in old age, it is difficult to speculate whether dynamic couplings would be stronger or weaker when using an emotion-based measure of well-being such as positive affect or negative affect. It is conceivable, however, that due to the strong relationship between extraversion and trait positive affect as well as between neuroticism and trait negative affect (Costa & McCrae, 1980), such initial level personality correlates may exert a stronger influence on dynamic relationships between aspects of cognitive functioning and emotional well-being.

We acknowledge that a common-cause explanation cannot be ruled out or directly examined and that the most powerful way to examine the influence of covariates would be to include them as time-varying entities in the dynamic system. The longitudinal data available in the BASE involves relatively few repeated measures and, as to be expected given the age of the sample, a sizeable amount of attrition over time. Given this, we chose to prioritize the robustness of the models, which would have been compromised by extensions of the dual change score model beyond the bivariate case (for a recent example, see Ghisletta & Lindenberger, 2005). Future studies need to carefully extend the bivariate space to include additional time-varying factors, such as those mentioned above (for a general discussion, see Freedman, 1987). Such endeavors are essential steps toward understanding dynamic lead–lag couplings between aspects of cognitive functioning and well-being during old and very old age more fully. These limitations aside, we take our results to provide initial indications that perceptual speed–well-being couplings have large effects on age-related change trajectories of perceptual speed but negligible effects on change in well-being and that these associations cannot be reduced to the set of antecedent conditions examined.[4]

Methodological Considerations

In the current study, we took advantage of the BDCSM that not only allows an examination of the dynamic associations between variables but also overcomes some of the limitations of related methods such as cross-lagged correlations (see also Rogosa, 1980). Specifically, the BDCSM accounts for differential reliabilities and stabilities of the variables examined, and it separates intraconstruct from interconstruct dynamics (cf. Ghisletta & Lindenberger, 2005; Lövdén et al., 2005). This technique also allows for a formal empirical comparison among different competing substantive hypotheses regarding the dynamic perceptual speed–well-being interplay. We nevertheless would like to highlight that any application of the BDCSM, in analogy to other multivariate-structural analyses, is based on untested statistical assumptions, including ergodicity (Molenaar, Huizenga, & Nesselroade, 2003) and sample homogeneity (Borsboom, Mellenbergh, & van Heerden, 2003). For instance, to make the model empirically identifiable, the dynamic couplings within and between constructs needed to be specified as population parameters (e.g., "fixed effects") with no variance, reflecting the strong assumption that these couplings are invariant across individuals.

In addition, three sets of methodological aspects deserve further elaboration. First, the consideration of state influencing subsequent change and its operational definition as deviations from a linear slope, as done in the present study, denotes but one of many approaches to study dynamic links within and between domains of functioning. Reasonable alternative specifications include, for example, an examination of how change in a given domain affects later change in another domain. The rationale underlying our approach was that state-subsequent change dynamics on the basis of a linear model reflect a reasonable balance between parsimony and the restricted longitudinal observation period.

Second, as is well known from other longitudinal studies (e.g., Schaie, 2005; Siegler & Botwinick, 1979), data incompleteness in the present data set was of nonrandom nature. One set of questions that arises from this clear violation of statistical assumptions asks whether the multiple layers of positive sample selection in BASE and its differential size in the two domains (e.g., T6 sample perceptual speed: 0.84 *SD*, well-being: 0.39 *SD*) may have biased our results. From our perspective, a reduction in the variance of one variable has, of course, direct implications for the generalizations to be drawn from this data set (e.g., underestimating true cognitive change). However, given the existence of highly reliable variance components for perceptual speed, it is difficult to see how (differential) selection could have conditioned the data in favor of finding the observed longitudinal supremacy of well-being over perceptual speed (cf. Ghisletta & Lindenberger, 2003). Also, both perceptual speed and well-being declined noticeably over time and showed similar rank-order stability, thereby decreasing the likelihood that the asymmetrical dynamic relation found was an artifact of differences in the relative stability of the two variables considered.[5]

A related set of questions relates to the capability of likelihood analyses to accommodate incomplete data. The MAR assumption allows for prior differences in level and observed change to predict subsequent participation, but it is violated when unobserved change differs from observed change (McArdle, 1994). As has been argued elsewhere (Lövdén et al., 2004; see also Feng, Silverstein, Giarrusso, McArdle, & Bengtson, 2006), unobserved change (for perceptual speed) can indeed be expected to be different from observed change in the BASE, but three reasons have repeatedly been put forward to highlight the relative robustness of likelihood analyses under MAR. To begin with, the magnitude of the selectivity effects of change is minor as compared to the effects of level. In addition, initial level is to some degree predictive of the missing value after dropout because data are correlated across measurement occasions. Finally, we have included the most attrition-informative variables in our models (i.e., age and perceptual speed), thereby enhancing the effectiveness of the FIML algorithm to accommodate incomplete data. Despite this general line of reasoning, we acknowledge that future statistical simulations are needed to explore the relative importance of differential sample attrition and assumption violations for parameter estimates (see also Hertzog, Lindenberger, Ghisletta, & von Oertzen, 2006; McArdle & Hamagami, 2001).

Third, the statistical properties of the BDCSM remain to be explored more fully. For example, as noted in the Results section, interpreting single parameters in the model (e.g., linear components of change) may at times be confusing because it requires considering other model parameters as well (e.g., auto-proportion parameters β, coupling parameters γ). To allow better interpretation of the joint implications of the fixed effects, we have found it helpful to graph the data in the ways reported here. In addition, in follow-up analyses we fixed both the beta and gamma parameters to zero, which corresponds to a typical linear latent growth curve model and thus provides estimates that might be more directly comparable to previous reports on change over time from BASE and other large-scale longitudinal studies (e.g., Kunzmann et al., 2000; Wilson et al., 2004). These analyses indicated substantial time-related decline for both perceptual speed (–1.67 biannual *T*-score units, $p < .001$) and well-being (–1.56 biannual *T*-score units, $p < .001$) after adjusting for age, health constraints, openness, and social participation.

[4] In a similar vein, additional follow-up analyses that (a) used the Digit Letter test (rather than the ability composite for perceptual speed) that has previously been found to be unaffected by repeated assessments of the same test (Lövdén, Ghisletta, & Lindenberger, 2004) or (b) included further measures of physical functioning (e.g., vision, auditory acuity) and personality (e.g., neuroticism, extraversion; for assessment details, see Smith & Baltes, 1999) yielded basically the same pattern of results as reported.

[5] Both perceptual speed and well-being not only displayed significant decline over time and variability in decline, but also showed comparable stability at the level of interindividual differences. Specifically, averaged autocorrelation coefficients for perceptual speed were $r = .70$, $p < .001$ (range from $r = .57$ to $r = .85$) and for well-being were $r = .62$, $p < .001$ (range from $r = .43$ to $r = .77$). This pattern also held after covarying out the effects of chronological age (perceptual speed: $r = .66$, $p < .001$; well-being: $r = .59$, $p < .001$). In addition, previous reports have documented that the BDCSM works effectively even if a relatively age-sensitive variable (e.g., perceptual speed) is the leading indicator of change in a relatively age-insensitive variable (e.g., word knowledge; cf. Ghisletta & Lindenberger, 2003).

In a related vein, the coupling parameters γ and the auto-proportion parameters β, as well as the effects of the covariates, are usually set to be equal across the time or age span considered (Ferrer & McArdle, 2004; Lövdén et al., 2005). In principle, this is a testable assumption in the model, for example, by comparing statistically nested models that either fix or freely estimate these parameters. Although this constitutes one of the model's strengths, reasons of simplicity as well as the limited observation period in most data sets often require equilibrium assumptions to increase the likelihood of model identification. The appropriateness of such a strategy may be of particular concern in age-based models because cross-domain associations found among the young old may not generalize to the oldest old (e.g., Baltes & Smith, 2003; Suzman, Manton, & Willis, 1992). In the present time-based model, we have included age information both as a continuous and as a dummy-coded covariate and results were effectively the same, suggesting that level and change differences with age in the two domains considered have not been the prime factor underlying our results.

Conclusions and Outlook

The current study sheds some light on dynamic lead–lag associations between perceptual speed and well-being during advanced old age. Future studies may more thoroughly exploit whether the modifying role of well-being for aspect of cognitive change holds across different periods of the life span or whether perceptual speed–well-being associations in early or mid-adulthood are better described by a leading role of perceptual speed, by bidirectional and transactional accounts, or by third-variable influence. Another line of future research would be to explore the extent to which between-person couplings as examined here are indicative of within-person associations (Röcke, 2006; Sliwinski, Hofer, & Smyth, 2004). For example, it is well known that between-person associations do not always map directly on within-person relationships (Cattell, 1957; Molenaar et al., 2003). Using microlongitudinal designs, the everyday dynamics of the coupling between facets of cognitive functioning and well-being can be examined more closely at the within-person level. Following these routes may also help to better understand how dynamic perceptual speed–well-being associations are embedded in the complex system of biological and cultural influences that operate over a given timescale. In this context, and in line with other recent analyses of longitudinal data (e.g., Ghisletta & Lindenberger, 2005; Lövdén et al., 2005), our study represents an initial effort to apply dynamic models to test empirically temporal hypotheses about lead–lag relations between level and change of functioning across psychological domains.

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Received January 19, 2006
Revision received January 22, 2007
Accepted February 7, 2007 ■