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Multivariate Longitudinal Modeling of Cognitive Aging:

Associations Among Change and Variation in Processing Speed and Visuospatial Ability

Annie Robitaille¹, Graciela Muniz², Andrea M. Piccinin¹, Boo Johansson³, and Scott M. Hofer¹

¹University of Victoria, Victoria, BC, Canada

²Medical Research Council Biostatistics Unit, Cambridge, UK

³Department of Psychology, University of Gothenburg, Gothenburg, Sweden

Abstract

We illustrate the use of the parallel latent growth curve model using data from OCTO-Twin. We found a significant intercept-intercept and slope-slope association between processing speed and visuospatial ability. Within-person correlations among the occasion-specific residuals were significant, suggesting that the occasion-specific fluctuations around individual's trajectories, after controlling for intraindividual change, are related between both outcomes. Random and fixed effects for visuospatial ability are reduced when we include structural parameters (directional growth curve model) providing information about changes in visuospatial abilities after controlling for processing speed. We recommend this model to researchers interested in the analysis of multivariate longitudinal change, as it permits decomposition and directly interpretable estimates of association among initial levels, rates of change, and occasion-specific variation.

Keywords

cognitive aging; longitudinal analysis; growth curve modeling; multivariate analysis

Research on cognitive aging involves describing aging-related change in cognitive functioning and explaining of age differences and aging changes by other theoretically fundamental variables (Dixon, 2011; Hertzog, 1985; Hultsch, Hertzog, Dixon, & Small, 1998; Rabbitt, 1993; Willett & Sayer, 1996). To date, most research has been cross-sectional in nature, examining individual differences in cognitive processes across people of different ages (see reviews by Salthouse, 1996; Verhaeghen & Salthouse, 1997). However, cross-sectional studies do not provide information about within-person aging-related change, which is of central importance for the development and evaluation of theories of cognitive aging. Longitudinal studies provide information about both between-person (interindividual) and within-person (intraindividual) change (Hultsch et al., 1998; Sliwinski & Buschke, 1999, 2004) and provide a common basis for comparison of between-person and within-person effects.

Developments in advanced statistical models and computer software (e.g., AMOS, Arbuckle 1983–2007; EQS, Bentler & Wu, 2005; PROC MIXED in SAS, Littell, Milliken, Stroup, & Wolfinger, 1996; Mplus, Muthén & Muthén 1998–2010a) for simultaneous modeling of two or more outcomes allow researchers to answer complex research questions and re-examine

cognitive aging theories (Ferrer & Ghisletta, 2011; Sliwinski & Mogle, 2008). These multivariate models can provide estimates of individual change in cognitive outcomes as a function of time (i.e., individual differences in slopes or rates of change), and also information on the degree to which change in different aging-related outcomes are associated. Applications of these models have been illustrated in recent books and articles (see Bollen & Curran, 2006; Curran, Obeidat, & Losardo, 2010; Duncan, Duncan, & Strycker, 2006; Grimm, 2007; Hofer et al., 2009; MacCallum, Kim, Malarkey, & Kiecolt-Glaser, 1997; Singer & Willett, 2003). Other examples, specifically related to cognitive aging, have examined whether individuals who show a decline in processing speed over time also decline in memory (MacDonald, Hulstsch, & Dixon, 2003; MacDonald, Hulstsch, Strauss, & Dixon, 2003; Sliwinski & Buschke, 1999, 2004; Zimprich, 2002). The parallel latent growth curve model (LCM) is one way in which two or more longitudinal outcomes have been simultaneously modeled (Bollen & Curran, 2006; Curran & Willoughby, 2003; Johansson et al., 2004; MacCallum et al., 1997; Tisak & Meredith, 1990; Willett & Sayer, 1994, 1996). See Curran, Stice, and Chassin (1997), Curran, Harford, and Muthén (1996); Hofer et al., (2009), and Stoolmiller (1994) for papers where parallel LCM were applied. For examples in cognitive aging, see Harvey, Beckett, and Mungas (2003) and Sliwinski, Hofer, Hall, Buschke, and Lipton (2003).

The purpose of this paper is to demonstrate the use of the parallel LCM and the directional LCM for the analysis of correlated and coupled change and to clarify the utility and distinction between these models. Longitudinal data from the Origins of Variance in the Oldest-Old: Octogenarian Twins (OCTO-Twin; Johansson & McClearn, 1996), which includes information about processing speed and visuospatial abilities, are used. The demonstration addresses the processing speed hypothesis which suggests that age-related changes in cognitive performance are accounted for by age-related changes in processing speed (Salthouse, 1996). We demonstrate the fit of the parallel LCM and discuss possible extensions of the model.

Parallel LCM

The parallel LCM is a direct extension of the univariate growth curve model to two or more outcomes. The essential difference lies in the joint modeling of the random effects and residual variance, permitting covariance estimates across outcomes. We begin by introducing the parallel LCM in terms of linear change and will discuss issues with alternative models of change in the discussion section. For a more detailed description of the univariate latent curve model see Bollen and Curran (2006), MacCallum et al., (1997), and Meredith and Tisak (1990). Equations 1 through 6 describe a linear parallel LCM. Level 1 (equations 1 & 4) and level 2 equations (2, 3, 5, & 6) for the parallel LCM with two covariates (gender & age at baseline) for visuospatial ability (y) and processing speed (x) are

$$y_{it} = \alpha_{0iy} + \alpha_{1iy}(Age_{it} - Age_{i1}) + \varepsilon_{it} \quad (1)$$

$$\alpha_{0iy} = \alpha_{00y} + \beta_{0y}(Age_{i1} - Age_{.1}) + \delta_{0y}(Gender_i) + v_{0iy} \quad (2)$$

$$\alpha_{1iy} = \alpha_{11y} + \beta_{1y}(Age_{i1} - Age_{.1}) + v_{1iy} \quad (3)$$

and

$$x_{it} = \alpha_{0iy} + \alpha_{1ix}(Age_{it} - Age_{i1}) + \varepsilon_{itx} \quad (4)$$

$$\alpha_{0ix} = \alpha_{00x} + \beta_{0x}(Age_{i1} - Age_{.1}) + \delta_{0x}(Gender_i) + v_{0ix} \quad (5)$$

$$\alpha_{1ix} = \alpha_{11x} + \beta_{1x}(Age_{i1} - Age_{.1}) + v_{1ix} \quad (6)$$

where y_{it} and x_{it} are visuospatial ability (Kohs Block Design) and processing speed (Symbol-Digit Substitution) scores for the i^{th} case at time t , (x or y) is the intercept for the i^{th} case, representing cognitive functioning for individual i at baseline; is the slope for the i^{th} case, representing rate of change in cognitive functioning over time, is the time-related variable (time since baseline) and ε_{it} is the residual specific to individual i and occasion t . α_{00} and α_{11} represent the mean intercept and slope for all cases. β_0 , β_1 and δ_0 represent the coefficients for the covariates of baseline age ($Age_{i1} - Age_{.1}$) and ($Gender_i$). Age_{i1} is age at time 1 for the i^{th} case and $Age_{.1}$ is the mean age at Time 1. In studies of aging where age heterogeneous samples are examined, it is important to include age at baseline as covariates of the intercept and slope in order to account for the fact that people of different ages are likely to have a different intercept and rate of change (see Sliwinski, Hoffman, & Hofer, 2010). v_{0i} and v_{1i} represent individual variability in the slope and intercept from the overall intercept and slope. Latent growth curve models assume that errors are normally distributed with a mean of zero and the covariance between the disturbances and between the disturbances and the intercept and slope are also assumed to be zero (Bollen & Curran, 2006).

The parallel LCM is useful for examining dynamic relationships in terms of covariances among intercepts, linear slopes, and occasion-specific residuals across different outcomes. This association between multiple outcomes is also referred to in the literature as correlated and coupled change (Hofer & Sliwinski, 2006; Hofer et al., 2009; Sliwinski & Mogle, 2008). Correlated change, for example, provides an estimate of association between the linear trajectory of processing speed and the linear trajectory of another cognitive performance variable (e.g., memory, visuospatial ability). In addition, the LCM estimates the joint association among occasion-specific residuals (OSRs) from each variable (Coupled change; Curran & Bauer, 2011; Hofer et al., 2009; Hoffman & Stawski, 2009; Sliwinski & Mogle, 2008). OSRs are within-person, time-specific deviations/fluctuations around people's long-term developmental trends on some outcome (Hofer et al., 2009; Martin & Hofer, 2004). The occasion-specific residuals are a combination of measurement error and circumstances specific to the measurement occasion. The distinction between the stable interindividual differences and the occasion-specific residuals is similar to the conceptual distinction between trait and state variance where trait variance is the difference between individuals as a result of stable characteristics of these people while state variance refers to fluctuation below or above the mean trend that are the result of situations specific to the measurement time. Researchers typically choose to constrain occasion-specific residual variances and covariances to be equal across time (Grimm, 2007). That is, the occasion-specific residual for each outcome can be specified to have a single variance across time and a single within-occasion covariance in the parallel case. This is the default specification for the parallel LCM using stacked data (i.e., estimated using multilevel modeling software).

Figure 1 illustrates a parallel LCM where outcomes X and Y (i.e., processing speed and visuospatial ability) are measured across five time points. The small circles with $Var(I_y)$, $Var(S_y)$, $Var(I_x)$, $Var(S_x)$ represent the residual variances of the intercepts and slopes that are unexplained by the covariates for outcomes X and Y , respectively.

Directional LCM

A variation of the parallel LCM is the directional LCM. This model estimates the structure of the latent factors by regressing the slope of one process (y) on the slope of the other (x) and the intercept of y on the intercept of x (Bollen & Curran, 2006). The structure of this model implies that processing speed predicts changes in Block Design (regression does not assume causality). This variation on the parallel LCM is shown in Figure 2.

Questions that can be explored with a parallel LCM and the directional LCM include:

1. What is the magnitude of the association between individual differences in the initial level (i.e., Time 1) of processing speed and visuospatial ability? This is similar to estimates from cross-sectional studies but is based on the model-based estimate of the intercept which maybe disattenuated for error if the longitudinal model is correct.
2. What is the magnitude of association between the linear rate of change of processing speed and the linear rate of change in visuospatial ability?
3. After accounting for linear change in processing speed and visuospatial performance, what is the magnitude of association among occasion-specific residuals across outcomes?
4. What is the proportion of variance explained in level and linear change in visuospatial ability that is accounted by processing speed (applies to the directional model specifically)? In age heterogeneous samples, the shared between-person age effect on intercept and slope can also be examined.

In the directional model, the slope of visuospatial ability can also be regressed on the intercept of speed (and vice versa, Bollen & Curran, 2006) in order to examine whether changes in memory could be accounted by initial speed levels. However, doing so assumes that the intercept is the point at which the process began which is rarely the case with aging research (Grimm, 2007). More realistically, in studies of lifespan development and aging, the intercept is complex and conditional on the process of change, the structure of time, and the age heterogeneity of the sample and, therefore, this question will not be explored here (see Curran et al., 1997; Curran et al., 1996 for examples of where this model has been applied).

Method

Illustrative Data

Data from the OCTO-Twin study (Johansson & McClearn, 1996) are used to illustrate the differences between the models. The OCTO-Twin study included dizygotic (DZ) and monozygotic (MZ) twin pairs aged 80 years and older. The sample was selected from older adults participating in the population-based Swedish Twin Registry (Cederlof & Lorch, 1978). The data include five cycles of longitudinal data collected every 2 years. The initial sample consisted of 702 individuals (351 same-sex pairs), of whom 225 were excluded because they had a diagnosis of dementia. A further 51 were excluded from the analysis because they were missing information on all outcome variables (Kohs Block Design and Digit-Symbol Substitution). A total of 426 participants were included in the final analyses. From the final sample of 426 participants, 136 no longer had their twin included in the study while 290 did (136 single twins and 145 twins pairs). The participants ranged from 79.42 to 92.94 years of age at time 1, with a mean age of 83.15; 278 (65%) were female and 148 (35%) were male.

Measures

Dementia—In order to identify individuals with dementia at each wave, multidisciplinary group consensus conferences were scheduled. The consensus conference used expertise from various disciplines to reach consensus about diagnosis and differential diagnosis, taking into account other health related conditions. The DSM-III-R criteria for dementia (American Psychiatric Association, 1987), NINCDS-ADRDA criteria for Alzheimer's disease (McKhann et al., 1984), and the NINDS-AIREN criteria for vascular dementia (Roman et al., 1993) were used.

Visuospatial Ability—Kohs Block Design Test (Dureman & Salde, 1959) was used. Respondents are shown cards with designs and instructed to replicate the patterns using colored blocks. Seven cards with white and red patterns are given to the participants, each with a maximum score of six, depending on the speed and accuracy of the solution. A score of zero is given if the allotted time is surpassed. The maximum score is 42.

Processing Speed—A modified (verbal rather than written) version of the Digit-Symbol Substitution Test was used to assess processing speed of participants. It is a performance subtest of The Wechsler Adult Intelligent Scale-Revised (Wechsler, 1991). Participants are given a record form with symbol-digit pairs followed by a series of digits. Participants are asked to provide a verbal response of the matching digit under each of the provided symbols as quickly as possible without skipping any numbers. Participants are given two 90-s trials to complete the task and are given one point for every correct symbol.

Analysis

Mplus version 6.1 was used for fitting all models (Muthén & Muthén, 1998–2010a). All input files are available by request to the authors. Given that twin data were used, we employed cluster identifiers to account for the dependency among sample participants (Stapleton, 2006). Using TYPE = COMPLEX with CLUSTER, standard errors and χ^2 test of model fit take into account the nonindependence of observations due to the cluster sampling of twin data (Muthén & Muthén, 1998–2010b).

Given that measurement intervals were very consistently spaced ($\pm$ approximately 2 weeks) and that Mplus does not provide standardized estimates when individually-varying time intervals are used (TSCORES and TYPE = RANDOM), we used fixed values for time (0, 2, 4, 6, 8). Mplus uses full information maximum likelihood (FIML) estimator (Enders, 2006) in the presence of missing values. With FIML, parameters are estimated directly from the available raw data on a case-wise basis, and the χ^2 test statistic and model fit indices are calculated from the log likelihood of the data for each observation (Duncan et al., 2006; Enders, 2006). The FIML procedure uses all available information to compute parameters (i.e., both partially complete and fully complete cases are used in the estimation), so that cases with partially missing data on the study variables can still be used in the analysis. Robust maximum likelihood (MLR) estimation was used given the clustered data (Muthén & Muthén, 1998–2010b; Yuan & Bentler, 2000). The MLR estimator, which is robust to nonnormality by providing adjusted χ^2 and standard errors, was used.

Results are reported for the model with age at study entry and gender included as covariates of the intercept, and age alone as covariates of the latent slope. For parsimony reasons, the slope was not regressed on gender given that it was not found as a significant covariate. Age was centered on mean age at time 1 ($Age_{t1} - Age_{t1}$).

Results

Univariate Latent Growth Curve Model

Table 1 presents the correlations, means, and variances for all study variables. Before estimating the multivariate models, we fitted univariate latent growth curve models for each cognitive variable. First, we tested linear models. To examine possible nonlinearity, we also fit quadratic latent curve models to the data. The univariate models were fit with and without covariates. For the unconditional models, the mean quadratic slope was significant for both visuospatial ability and processing speed, and random effects were significant for processing speed but not for visuospatial ability (see Table 2 for the parameter estimates). The instantaneous rate of change appears relatively flat (nonsignificant linear rate of change), and the negative quadratic estimate suggests an inverted-u shaped curve with a slight decrease in the magnitude of change over time. The nonsignificant variance component means that there is no significant individual variability in the quadratic trend. Comparison of the models with and without the quadratic trend suggested a better fit for the nonlinear models (see Table 3 for fit indices). For the conditional models, age and sex were not found to be significant predictors of the quadratic trend, and once these covariates were included in the model, there was no leftover variance in the quadratic curves (the regression intercept for the quadratic function was nonsignificant). Because of space limitations, in order to go in more detail about the linear model, and to simplify interpretation and illustration of results, linear-only models were used. It is complicated to interpret the relationship between two developmental processes using BLCM when quadratic functional forms are modeled. Furthermore, additional analyses are often required to better understand the results (i.e., possible high collinearity between linear and quadratic temporal metrics with a T1 centering). However, we acknowledge that ignoring the quadratic trend can have implications for the relationship between processing speed and visuospatial ability and future research that addresses the complications with modeling nonlinear functional forms in the context of the BLCM would be warranted (for more information about nonlinear latent growth curve models, see Blozis, 2007; Blozis, Conger, & Harring, 2007; Grimm, Ram, & Hamagami, 2011). Associations between parameters from complex models of change can also be estimated (e.g., processing speed = quadratic and visuospatial ability = linear; e.g., Curran et al., 2010) although the association between change functions is also difficult to interpret and alternative linear models (e.g., piecewise) are recommended. See Table 2 for the parameter estimates for the linear univariate growth curve models and Table 3 of the fit indices of all models.

Fixed and Random Effects

The fixed and random effects of the processing speed variable for the parallel LCM are identical to estimates from the directional LCM. Parameter estimates for visuospatial ability in the directional LCM, however, are conditional on the effects of age, sex, and processing speed. The between-person effect of age at baseline on initial visuospatial ability scores and on rate of change are no longer significant once processing speed is added to the model. The longitudinal fixed and random effects remain significant after regressing visuospatial abilities on speed, however, estimates are markedly reduced. See Table 4 for the standardized and unstandardized coefficients and Table 2 for the fit indices for the parallel LCM.

Covariances/Regressions

A significant positive relationship between the intercept of visuospatial ability and the intercept of processing speed was found. The slope-slope relationship was also significant, suggesting that the trajectory of visuospatial reasoning was related to the trajectory of processing speed, with steeper rate of change on verbal Digit Symbol test being associated

with a steeper rate of change on the Block Design. Furthermore, within-person correlations among the occasion-specific residuals were also significant, suggesting that the short-term fluctuations in individual's trajectories, after controlling for their rate of change, are related between the two outcomes. As expected, the standardized regressions of the directional LCM are identical to the correlations of the parallel LCM (see Table 4).

Discussion

Multivariate models are especially important for the analysis of longitudinal studies of aging given that they allow researchers to examine how multiple processes of change are associated. Using the parallel LCM, we identified a longitudinal association between performance on a Digit Symbol substitution task and a Block Design test. The directional LCM included regressions among the corresponding intercepts and slopes (rather than covariances), specifying that the rate of change of processing speed predicts the rate of change of visuospatial abilities. The conditional directional LCM also suggests that the latent slope and intercept of processing speed act as mediators between the covariates and the outcome (Bollen & Curran, 2006). The directional LCM aligns more closely with the processing speed hypothesis which predicts that age-related changes in cognition are accounted for by age-related changes in processing speed. However, this model is merely a variation of the parallel growth model and providing exactly the same fit to the data, and not providing a basis for determining causal direction or magnitude. Still, when it theoretically makes sense to have one variable predict another, regressions rather than correlations could be modeled between the growth factors. Although doing so does not alter the association (standardized regressions are identical to the correlations) between the processes, it nevertheless changes the interpretation and the estimates of the fixed and random effects of the predicted outcome variable (in this case visuospatial ability). Imposing a directed structure (regressing Block Design on Digit-Symbol) to the parallel LCM allowed us to explore between and within-person changes in visuospatial ability after controlling for variability explained by between and within-person change in speed of processing. That is, what are the cross-sectional and longitudinal effects of age/time on visuospatial abilities after controlling for speed?

Results for both correlated and coupled change were significant, suggesting that rates of linear change as well as occasion-specific deviations from the trends for processing speed and visuospatial abilities were associated. That is, over an 8-year period, older adults' individual differences in the rate of change on the processing speed task were related to individual differences on the visuospatial task. In addition, systematic occasion-specific deviations from the individual trends were also related, although this association was much weaker than the association between linear rates of change. Although occasion-specific residuals are often overlooked, these provide valuable information about developmental change between two or more variables that cannot be captured by correlated change alone (Hofer et al., 2009). Examining coupled change in addition to correlated change can result in an improved understanding of cognitive change processes and of short-term risk factors of cognitive decline, as well as a deeper understanding of aging theories. This model is especially pertinent for researchers interested in the association between two outcomes that both have an expected long-term trend over time (e.g., physical functioning and memory).

Of importance, this article was intended as a methods demonstration paper. The Digit Symbol test used not only measures speed but also memory and novel reasoning (Piccinin & Rabbitt, 1999). It is also possible that the Digit Symbol test also measures visuospatial ability given that the task requires that digits be matched with symbols. Individuals who are better than average at working with shapes might therefore find the processing speed task easier. Furthermore, Block Design test scores are based on accuracy but also on speed. The

similarities between both measures are important to consider before conclusions can be made about the longitudinal relationship between processing speed and visuospatial abilities.

Although the focus of the current paper was on the parallel LCM, other multivariate longitudinal models are also useful. For example, as mentioned above, other models include the growth curve model with a time-varying covariate (Bollen & Curran, 2006; Curran & Willoughby, 2003; Raudenbush & Chan, 1993), the dual change score model (DCSM; McArdle, 2001; McArdle & Hamagami, 2001), the autoregressive latent trajectory model (ALT; Bollen & Curran, 2006; Curran & Willoughby, 2003), and the factor-of-curves and curve-of-factors models (Duncan et al., 2006; McArdle, 1988). For example, the TVC model would provide information about the extent to which changes in the TVC (processing speed) directly affect occasion-specific deviations around the overall developmental trend/slope of cognition, but it does not take into account the latent growth curve of processing speed – and it does not provide information about the slope-slope and intercept-intercept covariance. The DCSM and the ALT models would provide information about the slope-slope and intercept-intercept covariance and provide information about the directionality of the processing speed and cognitive functioning relationship (McArdle, 2001; McArdle & Hamagami, 2001). An exhaustive description of all available models is beyond the scope of this paper. Researchers should keep in mind that model selection should be driven by the research question.

The parallel LCM can also be extended to simultaneously compare more than two variables (Fieuws & Verbeke, 2006; Fieuws, Verbeke, & Molenberghs, 2007). For example, these models could allow for examination of the relationship between cognition, physical functioning, and mental health. Given the computational demands for analyzing numerous outcomes simultaneously, a pairwise-fitting approach for multivariate modeling is recommended where (1) parallel models for all possible pair of outcomes are modeled and (2) all estimates for the parameters are combined (Fieuws & Verbeke, 2006; Fieuws et al., 2007).

As mentioned, the current paper modeled the parallel LCM using the latent growth curve (LGC) framework (McArdle, 1986; Meredith & Tisak, 1990; Willett & Sayer, 1994); however, these models can also be specified using multilevel modeling (Curran et al., 2010; Gibbons, Hedeker, & DuToit, 2010; Goldstein, 1987; Goldstein, 1995; MacCallum & Kim, 2000; MacCallum et al., 1997; Stoel & Garre, 2011; Stoel, Van den Wittenboer, & Hox, 2003). These are also referred to as the random-effects models (Laird & Ware, 1982), hierarchical models (Bryk & Raudenbush, 1987, 1992), random coefficient models (Rosenberg, 1973), and mixed models (Longford, 1987). In the multilevel format, all outcome variables (e.g., visuospatial ability and processing speed) are created as one outcome variable in the dataset. In order to take the multivariate nature of the model into account, dummy variables are created for each outcome variable (MacCallum et al., 1997). For example, the first dummy variable would have a value of one when the visuospatial ability is measured and otherwise a value of zero. Similarly, the second dummy variable would have a value of one when processing speed is measured and zero if not measured. The formula is therefore identical to the univariate model except for the additional subscript k to illustrate the multiple outcomes (MacCallum et al., 1997). Parameter estimates for both models are expected to be the same for MLM and SEM (Stoel et al., 2003; see MacCallum and colleague's, 1997, work for a detailed description as well as equations for this approach to multivariate modeling).

Additional issues for understanding multivariate growth involve the choice of the temporal metric and handling nonlinear change. Selecting a time metric (e.g., time since baseline, chronological age, time to death, time to diagnosis of dementia) that drives the change process is an important consideration for understanding individual and population change

(Hoffman, in press; Sliwinski, Hofer, & Hall, 2003; Sliwinski, Hofer, Hall et al., 2003; Sliwinski & Mogle, 2008). While the within-person model of change remains the same, the utility of alternative time metrics lies in the reorganization of individual differences in intercepts and slopes, which may better capture the population change and dynamics and make the analysis of individual differences more meaningful. The time-in-study model provides an index of time based on initial sample selection, with heterogeneity accounted for by time-invariant predictors as well as time-varying predictors, modeled as a separate growth process in this paper. The ability to decompose change processes into easily interpretable parameters of initial status, linear rate of change, and occasion-specific variation is a major strength of these growth curve models and their multivariate application.

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References

- American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders (DSM-III-R). 3. Washington, DC: Author; 1987. rev
- Arbuckle, J.L. Amos (Version 16.0). Chicago, IL: SPSS; 1983–2007. [Computer software]
- Bentler, P.M.; Wu, E. EQS (Version 6). Encino, CA: Multivariate Software; 2005. [Computer software]
- Blozis S.A. On fitting nonlinear latent curve models to multiple variables measured longitudinally. *Structural Equation Modeling*. 2007; 14:179–201.
- Blozis S.A, Conger K.J, Harring J.R. Nonlinear latent curve models for longitudinal data. *International Journal of Behavioral Development*. 2007; 31:340–346.
- Bollen, K.A.; Curran, P.J. Latent curve models: A structural equation approach. Hoboken, NJ: Wiley; 2006.
- Bryk A.S, Raudenbush S.W. Application of hierarchical linear models to assessing change. *Psychological Bulletin*. 1987; 101:147–158.
- Bryk, A.S.; Raudenbush, S.W. Hierarchical linear models in social and behavioral research: Applications and data analysis methods. 1. Newbury Park, CA: Sage; 1992.
- Cederlof, R.; Lorch, U. The Swedish Twin Registry. In: Nance, W.E.; Allen, G.; Parisi, P., editors. *Twin research: Biology and epidemiology*. New York: Alan R. Riss; 1978. p. 189–195.
- Curran P.J, Bauer D.J. The disaggregation of within-person and Between-person effects in longitudinal models of change. *Annual Review of Psychology*. 2011; 62:583–619.
- Curran P.J, Harford T.C, Muthén B.O. The relation between heavy alcohol use and bar patronage: A latent growth model. *Journal of Studies on Alcohol*. 1996; 57:410–418. [PubMed: 8776683]
- Curran P.J, Obeidat K, Losardo D. Twelve frequently asked questions about growth curve modeling. *Journal of Cognition and Development*. 2010; 11:121–136. [PubMed: 21743795]
- Curran P.J, Stice E, Chassin L. The relation between adolescent alcohol use and peer alcohol use: A longitudinal random coefficients model. *Journal of Consulting and Clinical Psychology*. 1997; 65:130–140. [PubMed: 9103742]
- Curran P.J, Willoughby M.J. Implications of latent trajectory models for the study of developmental psychopathology. *Development and Psychopathology*. 2003; 15:581–612. [PubMed: 14582933]
- Dixon, R.A. Enduring theoretical themes in psychological aging: Derivation, functions, perspectives, and opportunities. In: Schaie, K.W.; Sherry, L.W., editors. *Handbook of the psychology of aging*. 7. San Diego: Academic Press; 2011. p. 3–23.

- Duncan, TE.; Duncan, SC.; Strycker, LA. An introduction to latent variable growth curve modeling: Concepts, issues, and applications. 2. Mahwah, NJ: Erlbaum; 2006.
- Dureman, I.; Salde, H. Psykometriska och experimental-psykologiska metoderfor klinisk tillampning. Uppsala, Sweden: Almqvist & Wiksell; 1959.
- Enders, CK. Analyzing structural equation models with missing data. In: Hancock, GR.; Mueller, RO., editors. Structural equation modeling: A second course. Greenwich, CT: Information Age Publishing; 2006. p. 313-342.
- Ferrer, E.; Ghisletta, P. Methodological and analytical issues in the psychology of aging. In: Schaie, KW.; Sherry, LW., editors. Handbook of the psychology of aging. 7. San Diego: Academic Press; 2011. p. 25-39.
- Fieuws S, Verbeke G. Pairwise fitting of mixed models for the joint modeling of multivariate longitudinal profiles. *Biometrics*. 2006; 62:424–431. [PubMed: 16918906]
- Fieuws S, Verbeke G, Molenberghs G. Random-effects models for multivariate repeated measures. *Statistical Methods in Medical Research*. 2007; 16:387–397. [PubMed: 17656450]
- Gibbons RD, Hedeker D, DuToit S. Advances in analysis of longitudinal data. *Annual Review of Clinical Psychology*. 2010; 6:79–107.
- Goldstein, H. Multilevel models in educational and social research. London: Griffin; 1987.
- Goldstein, H. Multilevel statistical models. London: Edward Arnold; 1995.
- Grimm KJ. Multivariate longitudinal methods for studying developmental relationships between depression and academic achievement. *International Journal of Behavioral Development*. 2007; 31:328–339.
- Grimm KJ, Ram N, Hamagami F. Nonlinear growth curves in developmental research. *Child Development*. 2011; 82:1357–1371. [PubMed: 21824131]
- Harvey DJ, Beckett LA, Mungas DM. Multivariate modeling of two associated cognitive outcomes in a longitudinal study. *Journal of Alzheimer's Disease*. 2003; 5:357–365.
- Hertzog C. An individual differences perspective. *Research on Aging*. 1985; 7:7–45. [PubMed: 3903892]
- Hofer SM, Gray KM, Piccinin AM, Mackinnon A, Bontempo DE, Einfeld SL, Tonge BJ. Correlated and coupled within-person change in emotional and behavior disturbance in individuals with intellectual disability. *American Journal on Intellectual and Developmental Disabilities*. 2009; 114:307–321. [PubMed: 19928014]
- Hofer, SM.; Sliwinski, MJ. Design and analysis of longitudinal studies of aging. In: Birren, JE.; Schaie, KW., editors. Handbook of the psychology of aging. 6. San Diego: Academic Press; 2006. p. 1537
- Hoffman, L. Considering alternative metrics of time: Does anybody really know what “time” is?. In: Hancock, G.; Harring, JR., editors. Advances in longitudinal methods in the social and behavioral sciences. Charlotte, NC: Information Age Publishing; in press
- Hoffman L, Stawski R. Persons as contexts: Evaluating between-person and within-person effects in longitudinal analysis. *Research in Human Development*. 2009; 6:97–100.
- Hultsch, DF.; Hertzog, C.; Dixon, RA.; Small, BJ. Memory change in the aged. New York: Cambridge University Press; 1998.
- Johansson B, Hofer SM, Allaire JC, Maldonado-Molina M, Piccinin AM, Berg S, McClearn GE. Change in memory and cognitive functioning in the oldest-old: The effects of proximity to death in genetically related individuals over a six-year period. *Psychology and Aging*. 2004; 19:145–156. [PubMed: 15065938]
- Johansson, B.; McClearn, GE. Aging, environment and genetics: The OCTO Twin study of twins 80 and older: Presentation and progress. Institute of Gerontology, University College of Health Science; Jönköping, Sweden. [Technical report]
- Laird NM, Ware JH. Random-effects models for longitudinal data. *Biometrics*. 1982; 38:963–974. [PubMed: 7168798]
- Littell, RC.; Milliken, GA.; Stroup, WW.; Wolfinger, RD. PROC MIXED in SAS. New York: SAS Institute; 1996. [Computer software]

- Longford NT. A fast scoring algorithm for maximum likelihood estimation in unbalanced mixed models with nested random effects. *Biometrika*. 1987; 74:817–827.
- MacCallum, RC.; Kim, C. Modeling multivariate change. In: Little, TD.; Schnabel, KU.; Lindenberg, U., editors. *Modeling longitudinal and multiple-group data: Practical issues, applied approaches, and specific examples*. Mahwah, NJ: Erlbaum; 2000.
- MacCallum RC, Kim C, Malarkey WB, Kiecolt-Glaser JK. Studying multivariate change using multilevel models and latent curve models. *Multivariate Behavioral Research*. 1997; 32:215–253.
- MacDonald SWS, Hultsch DF, Dixon RA. Performance variability is related to change in cognition: Evidence from the Victoria Longitudinal Study. *Psychology and Aging*. 2003; 18:510–523. [PubMed: 14518812]
- MacDonald SWS, Hultsch DF, Strauss E, Dixon RA. Age-related slowing of Digit Symbol Substitution revisited: What do longitudinal age changes reflect? *Journal of Gerontology: Psychological Sciences*. 2003; 58B:187–194.
- Martin M, Hofer SM. Intraindividual variability, change, and aging: Conceptual and analytical issues. *Gerontology*. 2004; 50:7–11. [PubMed: 14654720]
- McArdle JJ. Latent variable growth within behavior genetic models. *Behavior Genetics*. 1986; 16:163–200. [PubMed: 3707483]
- McArdle, JJ. Dynamic but structural equation modeling of repeated measures data. In: Cattell, RB.; Nesselroade, J., editors. *Handbook of experimental psychology*. 2. New York: Plenum; 1988. p. 561–614.
- McArdle, JJ. A latent difference score approach to longitudinal dynamic structural equation analyses. In: Cudeck, R.; DuToit, S.; Sörbom, D., editors. *Structural equation modeling: Present and future*. Lincolnwood, IL: Scientific Software International; 2001. p. 342–380.
- McArdle, JJ.; Hamagami, F. Latent difference score structural models for linear dynamic analyses with incomplete longitudinal data. In: Collins, LM.; Sayer, AJ., editors. *New methods for the analysis of change*. Washington, DC: American Psychological Association; 2001. p. 139–175.
- McKhann G, Drachman D, Folstein M, Katzman R, Price D, Stadlan EM. Clinical diagnosis of Alzheimer's disease: Report of the NINCDS-ADRDA Work Group under the auspices of Department of Health and Human Services Task Force on Alzheimer's Disease. *Neurology*. 1984; 34:939–944. [PubMed: 6610841]
- Meredith W, Tisak J. Latent curve analysis. *Psychometrika*. 1990; 55:107–122.
- Muthén, LK.; Muthén, BO. Mplus (Version 6.11) [Computer software]. Los Angeles, CA: Muthén and Muthén; 1998–2010a.
- Muthén, LK.; Muthén, BO. Mplus user's guide. 6. Los Angeles, CA: Muthén and Muthén; 1998–2010b.
- Piccinin AM, Rabbitt PMA. Contribution of cognitive abilities to performance and improvement on a substitution coding task. *Psychology and Aging*. 1999; 14:539–551. [PubMed: 10632143]
- Rabbitt P. Does it all go together when it goes? The nineteenth Bartlett memorial lecture. *The Quarterly Journal of Experimental Psychology Section A*. 1993; 46:385–434.
- Raudenbush SW, Chan WS. Application of a hierarchical linear model to the study of adolescent deviance in an overlapping cohort design. *Journal of Clinical and Consulting Psychology*. 1993; 61:941–951.
- Roman GC, Tatemichi TK, Erkinjuntti T, Cummings JL, Masdeu JC, Garcia JH, Hofman A. Vascular dementia: Diagnostic criteria for research studies. Report of the NINDS-AIREN International Workshop. *Neurology*. 1993; 43:250–260. [PubMed: 8094895]
- Rosenberg B. Linear regression with randomly dispersed parameters. *Biometrika*. 1973; 60:61–75.
- Salthouse TA. The processing speed theory of adult age differences in cognition. *Psychological Review*. 1996; 103:403–428. [PubMed: 8759042]
- Singer, JD.; Willett, JB. *Applied longitudinal data analysis: Modeling change and event occurrence*. New York: Oxford University Press; 2003.
- Sliwinski M, Buschke H. Cross-sectional and longitudinal relationships among age, memory and processing speed. *Psychology and Aging*. 1999; 14:18–33. [PubMed: 10224629]

- Sliwinski M, Buschke H. Modeling intraindividual cognitive change in aging adults: Results from the Einstein Aging Studies. *Aging, Neuropsychology and Cognition*. 2004; 11:196–211.
- Sliwinski M, Hofer S, Hall C. Correlated cognitive change in older adults with and without preclinical dementia. *Psychology and Aging*. 2003; 18:672–683. [PubMed: 14692856]
- Sliwinski M, Hofer S, Hall CB, Buschke H, Lipton R. Modeling memory decline in older adults: The importance of preclinical dementia, attrition and chronological age. *Psychology and Aging*. 2003; 18:658–671. [PubMed: 14692855]
- Sliwinski MJ, Hoffman L, Hofer SM. Evaluating convergence of within-person change and between-person age differences in age-heterogeneous longitudinal studies. *Research in Human Development*. 2010; 7:45–60. [PubMed: 20671986]
- Sliwinski, M.; Mogle, J. Time-based and process-based approaches to analysis of longitudinal data. In: Hofer, SM.; Alwin, DF., editors. *Handbook on cognitive aging: interdisciplinary perspectives*. Thousand Oaks, CA: Sage; 2008. p. 477-491.
- Stapleton LM. An assessment of practical solutions for structural equation modeling with complex sample data. *Structural Equation Modeling*. 2006; 13:28–58.
- Stoel, RD.; Garre, FG. Growth curve analysis using multilevel regression and structural equation modeling. In: Hox, JJ.; Roberts, JK., editors. *Handbook of advanced multilevel analysis*. New York: Taylor & Francis Group; 2011. p. 97-111.
- Stoel RD, Van den Wittenboer G, Hox JJ. Analyzing longitudinal data using multilevel regression and latent growth curve analysis. *Metodologia de las Ciencias del Comportamiento*. 2003; 5:21–42.
- Stoolmiller M. Antisocial behavior, delinquent peer association, and unsupervised wandering for boys: Growth and Change from childhood to early adolescence. *Multivariate Behavioral Research*. 1994; 29:263–288.
- Tisak, J.; Meredith, W. Descriptive and associative developmental models. In: von Eye, A., editor. *Statistical methods in longitudinal research*. San Diego, CA: Academic Press; 1990. p. 387-406.
- Verhaeghen P, Salthouse TA. Meta-analyses of age-cognition relations in adulthood: Estimates of linear and nonlinear age effects and structural models. *Psychological Bulletin*. 1997; 122:231–249. [PubMed: 9354147]
- Wechsler, D. *The Wechsler intelligence scale for children*. 3. San Antonio, TX: The Psychological Corporation; 1991.
- Willett JB, Sayer AG. Using covariance structure analysis to detect correlates and predictors of change. *Psychological Bulletin*. 1994; 116:363–381.
- Willett, JB.; Sayer, AG. Cross-analyses of change over time: Combining growth modeling and covariance structure analysis. In: Marcoulides, GA.; Schumacker, RE., editors. *Advanced structural equation modeling: Issues and techniques*. Hillsdale, NJ: Erlbaum; 1996. p. 125-157.
- Yuan KH, Bentler PM. Three likelihood-based methods for mean and covariance structure analysis with non-normal missing data. *Sociological Methodology*. 2000; 30:165–200.
- Zimprich D. Cross-sectionally and longitudinally balanced effects of processing speed on intellectual abilities. *Experimental Aging Research*. 2002; 28:231–251. [PubMed: 12079576]

Figure 1.
Path diagram of the parallel LCM with two covariates and for five waves of data.

Figure 2. Path diagram of the directional LCM with two covariates and for five waves of data.

Table 1

Means, variances, and correlation for all study variables

	1	2	3	4	5	6	7	8	9	10	11	12
1. Block T1	51.0											
2. Block T2	0.78	46.3										
3. Block T3	0.76	0.84	44.7									
4. Block T4	0.71	0.76	0.80	48.9								
5. Block T5	0.71	0.75	0.74	0.77	49.5							
6. Speed T1	0.63	0.64	0.61	0.61	0.52	119.7						
7. Speed T2	0.62	0.71	0.66	0.68	0.62	0.79	112.3					
8. Speed T3	0.61	0.72	0.73	0.71	0.62	0.76	0.82	118.8				
9. Speed T4	0.57	0.67	0.66	0.75	0.66	0.69	0.78	0.77	121.2			
10. Speed T5	0.56	0.63	0.64	0.70	0.67	0.61	0.70	0.70	0.78	117.2		
11. Gender	0.04	0.04	0.08	0.07	0.08	0.03	0.09	0.06	0.07	0.02	0.23	
12. Age	-0.21	-0.22	-0.21	-0.26	-0.17	-0.23	-0.20	-0.23	-0.30	-0.27	0.06	7.6
Mean	11.90	11.76	11.37	10.25	9.08	24.20	23.99	23.43	21.65	18.83	0.65	83.15

Note. Variances are on the diagonal.

Table 2

Fixed and random effects for the linear and quadratic univariate latent growth models

Test	Intercept		Linear slope		Quadratic slope	
	Fixed	Random	Fixed	Random	Fixed	Random
Unconditional Block Design ^a	12.202 (0.38) *	39.86 (3.08) *	-0.29 (0.044) *	0.14 (0.057) *	-	-
Unconditional Block Design ^b	11.949 (0.39) *	41.72 (3.28) *	0.093 (0.12)	1.37 (0.51) *	-0.053 (0.015) *	0.018 (0.007) *
Unconditional Digit Symbol ^a	25.53 (0.63) *	95.80 (8.35) *	-0.44 (0.08) *	0.60 (0.14) *	-	-
Unconditional Digit Symbol ^b	24.94 (0.62) *	92.71 (8.44) *	0.37 (0.20)	1.85 (1.35)	-0.12 (0.028) *	0.028 (0.021)
Conditional Block Design ^a	11.59 (0.65) *	37.54 (3.0) *	-0.29 (0.045) *	0.132 (0.056) *	-	-
Conditional Digit Symbol ^a	24.85 (1.01) *	91.16 (8.13) *	-0.45 (0.083) *	0.59 (0.14) *	-	-

Note.

^a the linear model,

^b the quadratic model. Block Design, $N = 422$. Digit Symbol, $N = 375$. Covariates were included in the conditional models (age and sex on the intercept, and age on the slope) but are not reported in the table. Standard errors are in parenthesis.

* $p < .05$.

Goodness of fit statistics

Table 3

Model	df	χ^2	p	CFI	BIC	RMSEA	RMSEA 90% CI	
							Lower	Upper
Unconditional Block Design ^a	14	34.09	.002	0.98	7712.19	0.058	0.034	0.084
Unconditional Block Design ^b	10	11.40	.33	1.00	7714.52	0.018	0.000	0.058
Unconditional Digit Symbol ^a	14	38.05	.0005	0.96	7722.94	0.068	0.042	0.094
Unconditional Digit Symbol ^b	10	8.72	.56	1.00	7715.42	0.00	0.000	0.051
Conditional Block Linear ^a	21	38.34	.012	0.98	6576.15	0.044	0.021	0.066
Conditional Digsym Linear ^b	21	45.30	.0016	0.97	6842.521	0.056	0.033	0.078
Parallel LCM ^c	62	94.83	.0046	0.98	13986.45	0.035	0.020	0.049

Note. CFI = comparative index fit; RMSEA = root mean square error approximation; CI = confidence interval.

^a N = 422;

^b N = 375;

^c the parallel LCM is identical in fit to the directional LCM.

Table 4

Parameter estimates of the parallel and directional LCM

Models	Parallel LCM				Directional LCM			
	Block		Digit symbol		Block		Digit symbol	
	Estimate (SE)	SD	Estimate (SE)	SD	Estimate (SE)	SD	Estimate (SE)	SD
Fixed affect								
Intercept α_{00}	11.56 (0.65) *	1.82	23.77 (0.98) *	2.39	0.12 (0.77)	.019	23.77 (0.98) *	2.39
I on Age	-0.56 (0.13) *	.24	-0.88 (0.21) *	.24	-0.14 (0.11)	-.061	-0.88 (0.21) *	-.24
I on gender	0.89 (0.76)	.067	1.39 (1.17)	.067	0.22 (0.50)	.016	1.39 (1.17)	.067
Slope α_{11}	-0.30 (0.045) *	-.80	-0.53 (0.083) *	-.69	-0.16 (0.070) *	-.41	-0.53 (0.083) *	-.69
S on Age	0.008 (0.018) *	.060	-0.02 (0.034) *	-.071	0.014 (0.017)	.10	-0.020 (0.034) *	-.071
Random effects								
Var I v_{0i}	37.72 (3.029) *	.94	92.94 (8.25) *	.94	16.19 (1.96) *	.40	92.94 (8.25) *	.94
Var S v_{0i}	0.14 (0.057) *	.996	0.58 (0.13) *	.995	0.099 (0.050) *	.68	0.58 (0.13) *	.995
R e_{ii}	10.22 (0.67) *	.20-.22	24.69 (1.79) *	.20-.22	10.22 (0.67) *	.20-.22	24.69 (1.79)	.20-.22
Cov/Reg								
v_{0iy} with $v_{0ix}/I \alpha_{0iy}$ on I α_{0ix}	44.74 (4.42) *	0.76	-	-	0.481 (0.031) *	0.76	-	-
v_{1iy} with $v_{1ix}/S \alpha_{1iy}$ on S α_{1ix}	0.163 (0.064) *	0.56	-	-	0.28 (0.11) *	0.56	-	-
R e_{iy} with R e_{ix}	3.31 (0.78) *	0.21	-	-	3.31 (0.78) *	0.21	-	-

Note. I = Intercept; S = Slope; R = Occasion-specific residual; Var = Variance; Cov = Covariance; Reg = Regression. The standardized values for the residuals have a range of values rather than one value even though they were fixed over time given that standard deviations used in the calculation of standardized values are not stable over time.

* $p < .05$.