Examining Population Differences in Within-Person Variability in Longitudinal Designs Using Latent Variable Modeling: An Application to the Study of Cognitive Functioning of Older Adults

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Abstract

Longitudinal studies have steadily grown in popularity across the educational and behavioral sciences, particularly with the increased availability of technological devices that allow the easy collection of repeated measures on multiple dimensions of substantive relevance. This article discusses a procedure that can be used to evaluate population differences in within-person (intraindividual) variability in such longitudinal investigations. The method is based on an application of the latent variable modeling methodology within a two-level modeling framework. The approach is used to obtain point and interval estimates of the differences in within-person variance and in the strength of correlative effects of repeated measures between normal and very mildly demented persons in a longitudinal study of a diagnostic cognitive test assessing verbal episodic memory.

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Keywords

between-person variance, confidence interval, intraclass correlation coefficient, intraindividual variability, multilevel modeling, population difference, two-level study, within-person variance

Longitudinal designs have grown in popularity across the educational and behavioral sciences over the past several decades. This trend is to a large degree due to the increased availability of various technological devices that allow a researcher to repeatedly evaluate multiple dimensions of substantive interest over a relatively short period of time, as for instance in intensive longitudinal studies (e.g., Bolger & Laurenceau, 2013; Hamaker & Wichers, 2017; Walls & Schafer, 2006). An important issue that has arisen in such investigations is the adequate evaluation of the intraindividual variability of the studied subjects on the longitudinally administered measures. This within-person variance in each repeatedly assessed outcome variable represents the stability over time or lack thereof in the individual participants, and for that reason has attracted a great deal of attention (e.g., Grimm, Davoudzadeh, & Ram, 2017; Nesselroade & Molenaar, 2010; Watts, Walters, Hoffman, & Templin, 2016, and references therein). Interindividual differences in this variability, that is, in intraindividual development over time, and especially population differences in within-person or intraindividual variance, are of particular concern in many subject-matter domains. For example, these differences are of special importance when studying learning difficulties in elementary or middle school students, or mental retardation in children, or alternatively cognitive decline, or Alzheimer disease (AD) and related dementias in older adults, to name but a few important scientific areas of inquiry. Cognitive intraindividual variability, for instance, has been associated with vulnerability to decline (Bunce, Tzur, Ramchurn, Gain, & Bond, 2008), cerebral integrity or neurologic compromise (Hultsch, Strauss, Hunter, & MacDonald, 2008), and mortality risk (MacDonald, Hultsch, & Dixon, 2008). A main reason for the growing attention to within-person variability is the fact that those population differences may hold substantial potential with regard to enhancing accuracy of aimed diagnostic decisions (e.g., Dowling, Hermann, La Rue, & Sager, 2010).

The goal of the present article is to respond to this increased theoretical and empirical interest in intraindividual temporal change or lack thereof by discussing a readily available procedure for examining population differences in within-person variability. As a byproduct, the study of population differences in intraclass correlation coefficients (ICCs) becomes also straightforward to conduct (cf. Raykov, 2011). These coefficients are similarly of marked relevance in longitudinal investigations because they capture the extent to which the classical independence assumption is violated within person, by evaluating the degree to which there is clustering effect (correlation) of the repeated measures within examined individuals. For this reason, in addition to intra-individual variance, the ICCs are also important to use when assessing population differences in repeated measures studies, in particular when

interested in possible diagnostic decisions. We employ subsequently the outlined method for the purpose of examining subpopulation differences between persons with very mild dementia and normal persons based on repeated administrations of a popular clinical neuropsychological test, the Rey Auditory-Verbal Learning Test (AVLT; Rey, 1964). The AVLT measures verbal episodic memory and is often used to assess memory dysfunction severity and track changes over time. The test is designed as a list learning task in which an examinee is read aloud a 15-item word list and then is immediately asked to verbally recall as many words as possible in any order. The learning task is repeated five times in this study. We should note, however, that the discussed procedure has much wider applicability well beyond this empirical area of neuropsychological research.

Notation, Background, and Assumptions

In a two-level (multilevel) study, suppose that an approximately continuous measure is repeatedly administered to samples from two or more distinct populations. In this section, we discuss the method underlying the present article for the case of $g = 2$ subpopulations, and indicate that its extension to $g > 2$ populations is straightforward and involves no significant additional developments.

In this setting that is frequently of relevance in educational and behavioral research, denote an outcome measure of interest by Y_{ij} , where $i = 1, \dots, n_j$ is the index for the Level-1 units and $j = 1, \dots, J$ is that of Level-2 units, with J being the number of Level-2 units in a study under consideration ($n_j > 1, J > 1$; e.g., Hox, Moerbeek, & van de Schoot, 2017). With the nesting of Level-1 units within Level-2 units, the well-known unconditional two-level model is

$$Y_{ij} = \gamma_{00} + u_{0j} + r_{ij}, \quad (1)$$

where γ_{00} denotes the grand mean, u_{0j} the person-effect, and r_{ij} the Level-1 residual that as usual is assumed normally distributed with constant variance and uncorrelated with u_{0j} ($i = 1, \dots, n_j, j = 1, \dots, J$; e.g., Raudenbush & Bryk, 2002). Based on the variance decomposition that Equation (1) entails (e.g., Snijders & Bosker, 2012), the ICC is

$$\rho = \sigma_b^2 / (\sigma_b^2 + \sigma_w^2), \quad (2)$$

where σ_b^2 designates the between-group variance and σ_w^2 the within variance. Equation (2) contains parameters of particular relevance for the rest of this article. Their adjusted versions, on controlling for person differences in covariates of relevance, will also be used below.

A Latent Variable Modeling Procedure for Studying Population Differences in Within-Person Variability in Longitudinal Designs

Parameterizing Stability Over Time or Lack Thereof in a Longitudinal Design

In a longitudinal design setting (e.g., Bolger & Laurenceau, 2013), repeated measures are typically treated as nested within persons and thus represent Level-1 units, while

the studied individuals are treated as Level-2 units. A main quantity of theoretical and empirical interest in these designs, is the within-person variability represented in Equation (2) by the within-person variance σ_w^2 , since it indicates the stability over time or lack thereof in the temporal within-subject development. Specifically, large within-person variance would be expected with notable development over time in the repeated measure, that is, a potentially effective learning process, training, or practice effects, while smaller intraindividual variance is consistent with absence of learning, training, or practice effects (cf. Raudenbush & Bryk, 2002). The ICC ρ , as an index of violation of the classical independence assumption, reflects then the strength of correlation between the repeated measures for the same person, that is, the within-person correlation (clustering or nesting effect) of the repeatedly administered measure. Larger ICCs would be expected with lack of development or learning, training, or practice effects, while smaller ICCs can be observed with notable learning, training, or practice effects.

Hence, when concerned with population differences in within-person variability, both quantities σ_w^2 and ρ become parameters of main interest. Lack of identity across (sub)populations in these parameters, or the degree of their dissimilarity, indicate the extent of population differences in within-person variability over time, that is, in intraindividual development. These differences may be particularly relevant in the study of learning difficulties and learning disabilities, or in clinical settings for the assessment, monitoring, and possibly diagnosis of cognitive deficits that are typical in neurological disorders such as AD dementia (cf. Dowling et al., 2010).

A Latent Variable Modeling Procedure for Examining Population Differences in Within-Person Variability and Intraindividual Change

Following Raykov (2011), Equation (1) can be seen as containing in its right-hand side two latent variables, the Level-2 random effect u_{0j} and the Level-1 random effect r_{ij} ($i = 1, \dots, n_j, j = 1, \dots, J$). Hence, the unconditional model in Equation (1) can be seen as a latent variable model that can be fitted to data using the popular latent variable modeling (LVM; B. O. Muthén, 2002) methodology. As a result of this model fitting, point estimates with standard errors of the within-person variance (intraindividual variability) and between-person variance (interindividual variability) are obtained, as well as of the ICC. Following the initial transformation procedure outlined in Raykov and Marcoulides (2015; see also Raykov, Marcoulides, & Akaze, 2017), confidence intervals for each of these 3 parameters can be obtained within each of two (or more) independent populations. Then interval estimation of the population difference in the within-person variance (intraindividual variability) is achieved by considering the pertinent quantity

$$\Delta\sigma_w^2 = \sigma_{1w}^2 - \sigma_{2w}^2, \quad (3)$$

where σ_{1w}^2 and σ_{2w}^2 denote correspondingly these variances and are readily furnished employing the widely used delta method (e.g., Raykov & Marcoulides, 2004). This

method is implemented in the popular LVM software Mplus (L. K. Muthén & Muthén, 1998-2017), and is performed on user request after introducing an “external” parameter that is defined as the right-hand side of Equation (3) (cf. Raykov & Marcoulides, 2015; Raykov et al., 2017; see Appendix 1 for annotations and further details).

In the same way, in a following step interval estimation of the population difference in the ICCs

$$\Delta\rho = \rho_1 - \rho_2, \quad (4)$$

where ρ_1 and ρ_2 denote the corresponding ICCs, is rendered employing in the same manner the delta method on introducing another “external” parameter defined as the right-hand side of Equation (4) (see Appendix 2 and corresponding annotations for additional details).

The outlined procedure for examining population differences in within-person variance/intraindividual variability and the correlative or nesting effect of repeated measures in longitudinal designs, is applied in the next section to the study of normal versus mildly demented subpopulation differences using the AVLT as the outcome measure.

Examining Intraindividual Variability Differences in Normal and Mildly Demented Older Adults

Sample

For the aims of illustrating the utility and applicability of the discussed method for studying within-person variability, we used data that were obtained from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) database (www.adni.loni.usc.edu). The primary goal of ADNI has been to test whether imaging and other biological markers as well as clinical and neuropsychological assessment can be combined to measure the progression of mild cognitive impairment (MCI) and early AD. Determination of sensitive and specific markers of very early AD progression is intended to aid researchers and clinicians to develop new treatments and monitor their effectiveness as well as lessen the time and cost of clinical trials. To date, ADNI protocols have recruited more than 1,500 adults, aged 54 to 95 years, who are clinically diagnosed as cognitively normal, MCI, or AD. For up-to-date information on ADNI protocols, see www.adni-info.org. Data for this study were downloaded in September 2017. In the remainder of the present section, we use data from 1,393 participants ranging in age from 54 to 91 years (with a standard deviation [*SD*] of 7) who were classified at study entry as either cognitively “normal” (with a sample size $n_1 = 526$) or “very mildly demented” (with a sample size $n_2 = 867$) according to the Washington University Clinical Dementia Rating Scale (CDR; Morris, 1993). The CDR is commonly used in clinical and research studies to stage dementia severity (Hughes, Berg, Danziger, Coben, & Martin, 1982). The sample used in the

following analyses was predominantly Caucasian (92%), had an average education level of 16 years ($SD = 2.80$), and a gender composition of 55% female.

Procedure

To evaluate the differences in within-respondent variance (intraindividual variability) between the normal and mildly demented populations under investigation in this empirical study, we commence with the unconditional, saturated model (1). (Its two-group version, with no cross-group constraints, the external parameters for the difference in within-person variability and in the ICC, respectively, is fitted using the source code in Appendix 1.) The application of this approach yields the point and interval estimates in Table 1, with its last column displaying the associated 95% confidence intervals (for the first two and last four parameters obtained with the R-function in Appendix 3, which is included in this article for completeness purposes only; cf. Raykov & Marcoulides, 2015).

As seen from Table 1, the mildly demented group has significantly lower levels of within-person variability, which is consistent with the lack of effect of the repeated presentation of the stimuli (immediate learning trials) comprising the AVLT test. This finding shows a lack of practice and/or learning effects on the test and a diminished ability to acquire the 15 words across the learning trials. Similarly, this group has a significantly higher ICC, which is consistent with higher correlation of their repeated test scores over time. This stronger correlation in the mildly demented group is expected due to an impaired ability to improve performance across the serial learning trials.

In a second step, we use a conditional model that controlled for individual differences in gender, age, education, and Apolipoprotein epsilon 4 allele (APOE $\epsilon 4$), with the latter being a well-known genetic risk factor for AD often associated with episodic memory deficits (e.g., Wolk & Dickerson, 2010). This model allowed for subject-specific, or random, slopes (L. K. Muthén & Muthén, 1998-2017; the model is fitted using the source code in Appendix 2). The estimates of the conditional within-person variability and ICCs, along with their standard errors and confidence intervals (see also Appendix 3), are presented in Table 2.

As seen from Table 2, qualitatively the same results are obtained as with the unconditional approach (see Table 1) also when controlling for gender, age, education, and APOE $\epsilon 4$. That is, within a pair of normal and mildly demented adult subpopulations with the same age, gender, education, and APOE $\epsilon 4$, the demented group still has lower within-person variability and higher ICC. Both of these findings are consistent with their impaired memory retention abilities on the repeatedly presented trials of the used cognitive test (AVLT), with the qualification now that these differences are not a consequence of its results' (linear) relationship to gender, age, education, or APOE genotype.

Table 1. Parameter Estimates, Standard Errors, and Confidence Intervals for Unconditional Within-Person Variances and Intraclass Correlation Coefficients.

Parameter	Estimate	Standard error	t	Two-tailed p	95% confidence interval
NG ICC	0.244	0.023	10.501	<.001	[0.199, 0.290]
MDG ICC	0.446	0.018	25.119	<.001	[0.411, 0.481]
Within variance difference	2.827	0.283	9.974	<.001	[2.271, 3.382]
ICC difference	−0.202	0.029	−6.889	<.001	[−0.259, −0.144]
NG variance between	2.388	0.270	8.851	<.001	[1.859, 2.917]
NG variance within	7.386	0.236	31.340	<.001	[6.924, 7.848]
MDG variance between	3.670	0.251	14.614	<.001	[3.178, 4.163]
MDG variance within	4.560	0.157	28.971	<.001	[4.251, 4.868]

Note. See Appendix I for definition of parameters. NG = normal group; ICC = intraclass correlation coefficient; MDG = mildly demented group.

Table 2. Parameter Estimates, Standard Errors, and Confidence Intervals for Conditional Within-Person Variances and Intraclass Correlation Coefficients.

Parameter	Estimate	Standard error	t	Two-tailed p	95% confidence interval
NG ICC	0.187	0.022	8.437	<.001	[0.143, 0.230]
MDG ICC	0.382	0.019	20.243	<.001	[0.345, 0.419]
Within variance difference	2.826	0.283	9.973	<.001	[2.271, 3.381]
ICC difference	−0.195	0.029	−6.710	<.001	[−0.252, −0.138]
NG variance between	1.695	0.224	7.577	<.001	[1.257, 2.134]
NG variance within	7.386	0.236	31.342	<.001	[6.924, 7.848]
MDG variance between	2.816	0.210	13.381	<.001	[2.404, 3.228]
MDG variance within	4.560	0.157	28.971	<.001	[4.251, 4.868]

Note. See Appendix I for definition of parameters (here, after controlling for gender, age, education, and Apolipoprotein epsilon 4 allele [APOE ε4]). NG = normal group; ICC = intraclass correlation; MDG = mildly demented group.

Conclusion

The purpose of this article was to discuss a readily applicable latent variable modeling procedure for examining population differences in within-person or intraindividual variability as well as in within-person correlative effect in repeated-measure studies. The method furnishes population-specific point and interval estimates of within-person variance, which may be of particular interest in empirical studies concerned with capturing and examining population differences in intraindividual temporal development. The approach is readily employed using popular LVM software, and permits a researcher to shed light on a relevant aspect of the theoretically and

empirically important issue of population differences in temporal development. We would like to point out that the unconditional version of the procedure discussed in this article can be of particular interest in settings as a complementary approach to application of alternative methods for modeling intraindividual development over time. With this feature, the discussed method merits attention in empirical studies with complex patterns of change that cannot be readily simplified to a handful of parameters with uniform meaning across all members of a studied population(s).

The discussed procedure has several limitations that we would like to indicate here. One is the requirement of a large number of studied subjects (sample) from an examined subpopulation, since the method rests on an application of the two-level model in Equation (1), its conditional version, and maximum likelihood estimation. Some violations of normality that is assumed with the model are likely to be tolerated by this estimation method, and particularly its robust version (MLR; L. K. Muthén & Muthén, 1998-2017). We conjecture that the results of this robust method may be largely trustworthy also with a somewhat limited range of values taken by the response variable (repeated test or measure), for example, 10 or more, as long as their distribution is not excessively skewed (as with preponderance of responses at an end of the scale underlying the repeated measure). Similarly, the method used in this article does not assume that the respondents are themselves nested or clustered in higher order units (e.g., Level-3 units), but in our view, it may be expected to be robust to some relatively minor violations of this Level-2 unit independence assumption (particularly with close to normal response).

In conclusion, the present article intended to enrich the arsenal of educational and behavioral researchers involved in longitudinal studies, including intensive longitudinal studies that are becoming increasingly more popular in these sciences, with a readily and widely applicable procedure for point and interval estimation of population differences in intraindividual variability (within-person variability) and within-person correlative effect of repeatedly administered behavioral measures.

Appendix I

Mplus Source Code for Point and Interval Estimation of Population Differences in Unconditional Within-Person Variability and Intraclass Correlation Coefficient

```
TITLE:      EVALUATION OF POPULATION DIFFERENCES IN UNCONDITIONAL
            WITHIN-PERSON
            VARIABILITY AND ICC.

DATA:      FILE = <NAME OF RAW DATA FILE, IN 'VERTICAL' OR 'UNIVARIATE'
            FORMAT>;

VARIABLE:  NAMES = ID OCCASION CDGLOBAL MALE AGE EDUC APOE4 TRIAL;
            MISSING = ALL(-999);
            USEVARIABLE = TRIAL;
            CLUSTER = ID;
```



```

GROUPING = CDGLOBAL (0=NORMAL, 1=DEMENTED) ;
ANALYSIS:  TYPE = TWOLEVEL;
MODEL:     %WITHIN%
           TRIAL (N_W) ; ! WITHIN-PERSON VARIANCE IN NORMAL ADULTS.
           %BETWEEN%
           TRIAL (N_B) ; ! BETWEEN-PERSON VARIANCE.
MODEL DEMENTED:
           %WITHIN%
           TRIAL (D_W) ; ! WITHIN-PERSON VARIANCE IN MILDLY DEMENTED ADULTS.
           %BETWEEN%
           TRIAL (D_B) ; ! BETWEEN-PERSON VARIANCE.
MODEL CONSTRAINT:
           NEW(ICC_N, ICC_D, WV_DIFF, ICC_DIFF) ;
           ! INTRODUCING 'EXTERNAL' PARAMETERS OF RELEVANCE NEXT.
           ICC_N = N_B / (N_B + N_W) ; ! ICC IN NORMAL GROUP (SEE EQUATION (2)) .
           ICC_D = D_B / (D_B + D_W) ; ! ICC IN MILDLY DEMENTED GROUP.
           WV_DIFF = N_W - D_W ; ! POPULATION DIFFERENCE IN WITHIN-PERSON
           VARIANCE.
           ICC_DIFF = ICC_N - ICC_D ; ! POPULATION DIFFERENCE IN ICCs.
OUTPUT:    CINTERVAL ; ! USE R-FUNCTION IN APPENDIX 3 FOR CI FOR THE
           POPULATION
           ! VARIANCES (N_B, N_W, D_B, D_W) .

```

Note. Annotated comments provided after exclamation mark. This command file, like that in Appendix 2, assumes data are missing at random.

Appendix 2

Mplus Source Code for Point and Interval Estimation of Population Differences in Conditional Within-Person Variability and Intraclass Correlation Coefficient

```

TITLE:      EVALUATION OF POPULATION DIFFERENCES IN UNCONDITIONAL
           WITHIN-PERSON
           VARIABILITY AND ICC.
DATA:       FILE = <NAME OF RAW DATA FILE, IN 'VERTICAL' OR 'UNIVARIATE'
           FORMAT> ;
VARIABLE:   NAMES = ID OCCASION CDGLOBAL MALE AGE EDUC APOE4 TRIAL;
           MISSING = ALL(-999) ;
           USEVARIABLE = TRIAL;
           CLUSTER = ID;
           GROUPING = CDGLOBAL (0=NORMAL, 1=DEMENTED) ;
ANALYSIS:   TYPE = TWOLEVEL RANDOM;
MODEL:      %WITHIN%
           TRIAL (N_W) ;
           %BETWEEN%
           TRIAL ON MALE AGE EDUC APOE4;
           TRIAL (N_B) ;

```

```

MODEL DEMENTED:
    %WITHIN%
    TRIAL (D_W) ;
    %BETWEEN%
    TRIAL ON MALE AGE EDUC APOE4;
    TRIAL (D_B) ;

MODEL CONSTRAINT:
    NEW(ICC_N, ICC_D, WV_DIFF, ICC_DIFF, W_SD_DIF);
    ICC_N = N_B / (N_B + N_W) ;
    ICC_D = D_B / (D_B + D_W) ;
    WV_DIFF = N_W - D_W;
    ICC_DIFF = ICC_N - ICC_D;
    W_SD_DIF = SQRT(N_W) - SQRT(D_W) ;

OUTPUT:    CINTERVAL;

```

Appendix 3

R-Function for Interval Estimation of Population-Specific Within-Person and Between-Person Variance

```

ci.wp_bp_var = function(gvd, se){
  l = log(gvd) # get variance estimate from output of code in Appendix 1.
  sel = se/gvd # get its associated S.E. from that output, too.
  ci_l_lo = l - 1.96*sel # routine CI construction for logged variance.
  ci_l_up = l + 1.96*sel
  ci_lo = exp(ci_l_lo) # back-transforming for lower endpoint of variance CI
  ci_up = exp(ci_l_up) # back-transforming for upper endpoint of variance CI
  ci = c(ci_lo, ci_up)
  ci # print to screen obtained variance CI.
}

```

Note. This R-function is identical to the R-function “ci.gvd” in Raykov and Marcoulides (2015) (apart from name) and is presented here merely for completeness of the present article.

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References

- Bolger, N., & Laurenceau, J.-P. (2013). *Intensive longitudinal methods: An introduction to diary and experience*. New York, NY: Guilford Press.
- Bunce, D., Tzur, M., Ramchurn, A., Gain, F., & Bond, F. W. (2008). Mental health and cognitive function in adults aged 18 to 92 years. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 63, P67-P74.
- Dowling, N. M., Hermann, B., La Rue, A., & Sager, M. (2010). An examination of the latent structure of the neuropsychological test battery of the Wisconsin Registry for Alzheimer's Prevention. *Neuropsychology*, 24, 742-756.
- Grimm, K., Davoudzadeh, P., & Ram, N. (2017). IV. Developments in the analysis of longitudinal data. *Monographs of the Society for Research in Child Development*, 82, 46-66.
- Hamaker, E. L., & Wichers, M. (2017). No time like the present: Discovering the hidden dynamics in intensive longitudinal data. *Current Directions in Psychological Science*, 26, 10-15.
- Hox, J. J., Moerbeek, M., van de Schoot, R. (2017). *Multilevel analysis: Techniques and applications* (3rd ed.). New York, NY: Routledge.
- Hughes, C. P., Berg, L., Danziger, W. L., Coben, L. A., & Martin, R. L. (1982). A new clinical scale for the staging of dementia. *British Journal of Psychiatry*, 140, 566-572.
- Hultsch, D. F., Strauss, E., Hunter, M. A., & MacDonald, S. (2008). Intraindividual variability, cognition, and aging. In F. I. M. Craik & T. A. Salthouse (Eds.), *The handbook of aging and cognition* (pp. 491-556). New York, NY: Psychology Press.
- MacDonald, S., Hultsch, D. F., & Dixon, R. A. (2008). Predicting impending death: Inconsistency in speed is a selective and early marker. *Psychology and Aging*, 23, 595-607.
- Morris, J. C. (1993). The Clinical Dementia Rating (CDR): Current version and scoring rules. *Neurology*, 43, 2412-2414.
- Muthén, B. O. (2002). Beyond SEM: General latent variable modeling. *Behaviormetrika*, 29, 81-117.
- Muthén, L. K., & Muthén, B. O. (1998-2017). *Mplus user's guide* (8th ed.). Los Angeles, CA: Muthén & Muthén.
- Nesselroade, J. R., & Molenaar, P. C. M. (2010). Emphasizing intraindividual variability in the study of development over the lifespan. In W. F. Overton (Ed.), *Handbook of life-span development: Vol. 1. Cognition, biology, and methods across the lifespan* (pp. 30-54). Hoboken, NJ: Wiley.
- Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.
- Raykov, T. (2011). Intra-class correlation coefficients in hierarchical designs: Evaluation using latent variable modeling. *Structural Equation Modeling*, 18, 73-90.
- Raykov, T., & Marcoulides, G. A. (2004). Using the delta method for approximate interval estimation of parametric functions in covariance structure models. *Structural Equation Modeling*, 11, 659-675.
- Raykov, T., & Marcoulides, G. A. (2015). A direct latent variable modeling-based method for point and interval estimation of coefficient alpha. *Educational and Psychological Measurement*, 75, 146-156.
- Raykov, T., Marcoulides, G. A., & Akaze, H. O. (2017). Comparing between- and within-group variances in a two-level study: A latent variable modeling approach to evaluating their relationship. *Educational and Psychological Measurement*, 77, 351-361.

- Rey, A. (1964). *L'examen clinique en psychologie* [The clinical examination in psychology]. Paris, France: Presses Universitaires de France.
- Snijders, T., & Bosker, R. (2012). *Multilevel analysis: An introduction to basic and applied multilevel analysis* (2nd ed.). Thousand Oaks, CA: Sage.
- Walls, T. A., & Schafer, J. L. (Eds.). (2006). *Models for intensive longitudinal data*. New York, NY: Oxford University Press.
- Watts, A., Walters, R. W., Hoffman, L., & Templin, J. (2016). Intra-individual variability of physical activity in older adults with and without mild Alzheimer's disease. *PLoS One*, *11*, e0153898.
- Wolk, D. A., & Dickerson, B. C. (2010). Apolipoprotein E (APOE) genotype has dissociable effects on memory and attentional-executive network function in Alzheimer's disease. *Proceedings of the National Academy of Sciences U S A*, *107*, 10256-10261.