Exploring the Relations Among Different Levels of Intraindividual Variability and Longitudinal Change Using a Mixed Effects Location Scale Model

Philippe Rast* Stuart W. S. MacDonald*

Abstract
The investigation of within-person variability has increased in recent years and has proven be a fruitful field in the investigation of cognitive change. At the same time, intensive measurement designs have become more and more important because they allow the estimation of within-person effects. Here, within-person variability is estimated with a mixed effects location scale model. That model allows one to include explanatory variables at the within- and between-person level and it estimates random effects in the location and scale part simultaneously. We used this model in a Bayesian framework to demonstrate its application to three level data. 304 participants have been measured on a reaction time test at four bursts, each one year apart. Each burst contained four sessions of weekly (1 to 2 weeks apart) measurements. We found considerable individual differences among participants in all parameters. The location and scale parameters were not independent whereby the random scale parameters correlated with the random intercept of the location part of the model.

Key Words: Intensive Measurement Design, Location Scale Model, Variance Modeling, Mixed Effects

1. Intraindividual Variability

Research on intraindividual variability has received increasing attention in different areas such as cognition, affect and, broadly speaking, neuroscience. The basic idea is that within-person variability which has typically been relegated to the error term still carries some systematic components which can be either described and predicted or which are used as predictors.

Within-person variability can be obtained from longitudinal data but studies based on widely spread multi-wave designs typically lack temporal resolution on the lower scale and are not sensitive to within-person dynamics, changes, or events that occur between assessments (cf. Rast et al., 2012b; Sliwinski, 2008). Intensive measurement designs are necessary to obtain better temporal resolution and to address within-person changes on different time scales (Rast and Hofer, in press; Walls et al., 2011). These design also mirror the distinction made between "microdevelopment", that is, development within a short time frame, as opposed to "macrodevelopment," which typically covers development over longer time spans (Yan and Fischer, 2002). Especially critical is the temporal sampling when the focus is on within-person variability because the sampling intervals also determine the quality and interpretation of the variability measure.

Intensive measurement designs use a mix of very closely spaced assessments (i.e., bursts) to model short-term effects and widely spaced waves to capture longer term effects such as, for example, aging-related changes (Nesselroade, 1991). Together with daily diary and ecological momentary assessments (EMA), measurement burst designs provide data on short terms such as hours, days, or weeks. In addition

*University of Victoria, Dept. of Psychology, P. O. Box 1700, Victoria, BC, V8W 2Y2, Canada

they also provide data on longer term changes such as month or years and as such offer the possibility to examine within-person changes. The pairing of multi-burst designs and informative measurement models allows the separation of short- from long-term processes which operate across different time scales.

These type of data offer new possibilities to examine within-person variation and change but they also add additional complexity to statistical modeling. Measurement burst data deliver at least three- and oftentimes four and more levels of analysis which need to be taken into account in the statistical model.

Recently, interest in within-person variability has increased and evidence suggests that within-person variability (also termed (in)consistency) can account for developmental changes (Yan and Fischer, 2002). Although these ideas are not new (cf. Fiske and Rice, 1955), there has been rising interest in understanding the role of within-person variability. Generally, more variability in repeatedly administered responses is seen to reflect behavioral inconsistency and with it a trend to decline in performance up to several years later (cf. Bielak et al., 2010; MacDonald et al., 2003). MacDonald et al. (2006) suggested that the degree to which individuals vary in their behavior may reflect alterations at a systems or a cellular level in the brain. In that case, intraindividual variability may provide information about a possible underlying pathology or, in the worst case, impending death (MacDonald et al., 2008).

The extraction of intraindividual variability is, however, not without controversy. Up to date, the most common way to address inconsistency is the estimation of intraindividual variability (iiV) or intraindividual standard deviations (iSD) (e.g. Hultsch et al., 2002). The usual approach to obtain estimates of intraindividual variability in repeated data is to detrend or filter the data in order to remove time-related trends. In a following step, the remaining fluctuations captured by the residual terms are used to estimate the degree of individual variability. Hence, the investigation of intraindividual variability is treated as, at least, a two-step approach where it is assumed implicitly that the requirements put on the data are met. That is, that data observations are locally independent and identically distributed (Ram and Gerstorf, 2009). The question which remains typically unanswered is whether the assumption of independent and identically distributed observation reflects the human behavior adequately. As has been discussed recently, these assumptions may not be appropriate especially for variables which tend to produce heteroscedastic and skewed error distributions.

The technique to analyze or detrend data are usually based on some form of the general linear model which posits normally distributed residuals which, however, does not necessarily represent the distribution of the residuals in the data. This can be problematic if the distribution of the residuals is heavily skewed which may be the case in a number of psychological variables which tend to produce skewed residual distributions, such as distributions from scores in depression scales or from reaction time (RT) data. In fact, a common finding in RT data is that the variance is not constant but changes as a function of the mean, that is, the variance is heteroscedastic (Hick, 1952). Wagenmakers and Brown (2007), for example, investigated the relation between the mean and standard deviation of RTs and found strong evidence of a linear relation among the first and the second moment of the distribution. Moreover, Schmiedek et al. (2009) investigated the relation between intraindividual means (iM) and iSD of a RT distribution by fitting different models to a sample of young and old participants. They concluded that in the younger group, and to a smaller extent in the older group, the relation between the iM and the iSD was positive and nonlinear. A similar relation has been observed in older adults RT performance, where the mean RT and the associated variability typically increases with advancing age (e.g. Myerson et al., 2007). This problem has been acknowledged for some time especially in the RT literature and a number of researchers addressed the issue of dependent mean and variance by proposing different distributions underlying the data, of which the most prominent are the (shifted) Weibull, the ex-Gaussian or the log-normal distribution (Hedeker and Mermelstein, 2007; Heathcote and Brown, 2002; Myerson et al., 2007; Wagenmakers and Brown, 2007). Currently, however, most researchers rely on the two-(or more)-step procedure to extract intraindividual variability estimates with distribution related issues typically ignored. At the same time, new methods have advanced in this field which enable one to estimate inter- and intraindividual variability simultaneously and which can also make use of, for example, log-normal or Gamma distributions.

1.1 Mixed Effects Location Scale Model

Such a model has been proposed by Hedeker et al. (2008) who referred to it as mixed effects location scale model as it estimates the location (i.e., means) and scale (i.e., variances) and allows the incorporation of concomitant variables both at the between- and the within-person level. The authors used this model to investigate mood of adolescent smokers using ecological momentary assessments (EMA) data. With this technique they were able to show that mood variability decreased after smoking events. Recently, Rast et al. (2012a) used this model to investigate the relation among daily stressors and variability in positive and negative affect. The authors found differential effects in mood variability, with participants who were variable in mood being differently affected by stressors compared to participants who were consistent in their daily variation in mood. Rast and Zimprich (2011) used the location scale model to estimate within-person variance in an RT task. Age and reaction times in another processing speed task were used to predict within-person variability. The authors used the average, individual RT as a predictor to account for larger variability in RT due to, on average, slower RTs.

The mixed effect location scale model has been mostly used in two-level data. Given that measurement burst data consists of more than two levels, we present an extension of this model for a three-level situation in a Bayesian framework.

2. Methods

2.1 Example data from Project MIND

In order to illustrate the application of the three-level mixed effects location scale model we use data from an intensive measurement burst design study Project MIND (e.g., Hultsch et al., 2008), a study based on 304 community-dwelling adults (208 women and 96 men) ranging in age from 64 to 92 years ($M = 74.02$, $SD = 5.95$). Participants were recruited through advertisements in the local media (newspaper and radio) requesting healthy community-dwelling volunteers who were concerned about their cognitive functioning. All participants were Caucasian. Exclusionary criteria included a diagnosis of dementia by a physician or a Mini Mental Status Examination (MMSE Folstein et al., 1975) less than 24, a history of significant head injury (defined as loss of consciousness for more than 5 minutes), other neurological or major medical illnesses (e.g., Parkinsons disease, heart disease, cancer), severe sensory impairment (e.g., difficulty reading newspaper-size print, difficulty hearing a normal conversation), drug or alcohol abuse, a current psychiatric diagnoses, psychotropic drug use, and lack of fluency in English.

For the present work, we selected the first four bursts, each one year apart. Each burst contained four sessions of weekly (1 to 2 weeks apart) measurements. In each burst, the sessions within the bursts are scaled in terms of weeks, with the bursts scaled in years. Age of the participants was grand mean centered at 74.02 years.

2.2 Materials

2.2.1 Digit Symbol

Processing speed was assessed using the WAIS-R Digit Symbol Substitution task Wechsler (1981). Participants were presented with a coding key pairing nine numbers (1 through 9) with nine different symbols. Printed under the coding key were rows of randomly-ordered numbers with empty boxes below. Participants were given 90 seconds to transcribe as many symbols as possible into the empty boxes based on the digit-symbol associations specified in the coding key. The number of correctly completed items represented the outcome measure.

2.2.2 Choice reaction time 1-back (CRT)

This RT task served as the dependent variable in our analyses. Participants received a warning stimulus consisting of a horizontal row of four plus signs on the screen. The response keyboard had four keys in a horizontal array corresponding to the display on the screen. After a delay of 1s, one of the plus signs changed into a box. The location of the box was randomly equalized across trials. Participants were instructed to press the key corresponding to the location of the box on the previous trial as quickly as possible. Although the instructions emphasized speed, participants were also instructed to minimize errors. A total of 10 practice trials and 61 test trials were administered. Because participants made no response on Trial 1, the latencies and percent correct of the remaining 60 test trials were actually used for analysis. Due to the skewed nature of CRT we log-transformed the CRT responses.

2.3 Model specification

The LSM permits the use of explanatory variables for both between-person variance as well as for individual differences in within-person variation. Further, it estimates all model parameters and correlations among random effects simultaneously and retains the location and scale information.

The mixed effects location scale model presented by Hedeker et al. (2008) is based on previous work done by Lindley (1971), Leonard (1975) and Cleveland et al. (2002). The standard linear mixed effects model with repeated measurement in $j\,(j = 1, 2, ..., J_k$ bursts) and $i\,(i = 1, 2, ..., I_k)$ sessions, may be specified as (see also Rast et al., 2012a)

$$\mathbf{y}_k = \mathbf{X}_k'\boldsymbol{\beta} + \mathbf{Z}_k'\mathbf{b}_i + \boldsymbol{\epsilon}_k, \tag{1}$$

where $\mathbf{y}_k$ is the $J_k I_k \times 1$ response vector for observations in person k. $\mathbf{X}_k$ is the $J_k \times p$ design matrix for the fixed effects for observations in person k. $\boldsymbol{\beta}$ captures the fixed effects and its dimension is $p \times 1$. The random effects are in the $J_i \times q$ matrix $\mathbf{Z}_k$ for observations in person k where $\mathbf{b}_k$ is the according $q \times 1$ vector with the random effects coefficients. $\boldsymbol{\epsilon}_k$ is a vector of errors specific to person k. The general assumption in these models is that random effects follow a normal distribution with mean $\mathbf{0}$ and variance $\mathbf{\Phi}$. Where $\mathbf{\Phi}$ is a $q \times q$ covariance matrix for the random effects with the variances σ_b^2 and the covariances $\sigma_{bb'}$. The errors $\boldsymbol{\epsilon}_k$ are also assumed to be normally distributed with a mean of $\mathbf{0}$ and covariance of $\sigma_\epsilon^2 \mathbf{\Psi}_k$ where $\mathbf{\Psi}_k$ is a $n_k \times n_k$ matrix which can take different structures. In these models the between-person (BP) variance is captured by σ_b^2 and the within-person (WP) variance is represented in σ_ϵ^2.

In order to allow the error variance to differ at the individual, burst, and session level, we add the subscripts ijk to the WP variance term and obtain $\sigma^2_{\epsilon_{ijk}}$ In the next step, we may add time-varying covariates $\mathbf{W}_{ijk}$ for the fixed effects and $\mathbf{V}_{ijk}$ for the random effect to influence the WP variance estimate:

$$\sigma^2_{\epsilon_{ijk}} = \exp(\mathbf{W}'_{ijk}\boldsymbol{\tau} + \mathbf{V}'_{ijk}\mathbf{t}_k). \tag{2}$$

$\boldsymbol{\tau}$ is comparable to the regression weights $\boldsymbol{\beta}$ in Equation 1, that is, τ_0 defines the average WS variance and τ_1 weights the influence of the predictor on the variance. The individual departures from the fixed effects which are captured in the random effects $\mathbf{t}$ are normally distributed with mean 0 and variance σ_t^2. The use of the exponential function ensures that the variance estimate is positive (cf. Hedeker et al., 2008, 2009) but it also posits that $\sigma^2_{\epsilon_{ij}}$ is log-normally distributed. Here, one might choose another distribution such as the commonly used inverse-Gamma distribution

Given that we use a Bayesian framework to specify the LSM we need to define distributions for the priors and hyperpriors. With the assumption that the random effects are from a normal distribution and the error variance from a log-normal distribution we previously defined the prior distribution in the Bayesian sense. The hyperpriors for the mean of the intercept and slope terms are multivariate normally distributed and, in order to ensure that the covariance matrix of the random effects is symmetric and positive definite we use a scaled inverse-Wishart distribution, $scaled - inverse - Wishart(\mathbf{R}, k)$ (cf. Gelman and Hill, 2007) defined by two parameters as the prior. The matrix $\mathbf{R}$ can be interpreted as the prior estimate of the covariance matrix and with degrees of freedom k which define the weight one gives the prior $\mathbf{R}$ (cf Gelman and Hill, 2007; Gelman, 2006; Hamaker and Klugkist, 2011). In the following we use Lynch's (2007) notation to represent the multilevel structure of the mixed effect location scale model. The baseline model with only time-variables at different scales (i.e., weekly sessions, and yearly bursts) is defined as

$$\begin{aligned}
&\text{Level 1:}\\
&\quad y_{ijk} \sim N(\mu_{ijk}, \sigma^2_{\epsilon_{ijk}})\\
&\quad \mu_{ijk} = \alpha_{0jk} + \alpha_{1jk}\text{Session}_{ijk} + \alpha_{2jk}\text{Burst}_{jk} + \beta\text{Session}_{ijk}\text{Burst}_{jk}\\
&\quad \sigma^2_{\epsilon_{ijk}} = \exp(\tau_{0k} + \tau_{1k}\text{Session}_{ijk} + \tau_{2k}\text{Burst}_{ijk} + \lambda\text{Session}_{ijk}\text{Burst}_{jk})\\
&\text{Level 2:}\\
&\quad \begin{bmatrix}\mu_{\alpha_{0j}}\\ \mu_{\alpha_{1j}}\end{bmatrix} \sim N\left(\begin{bmatrix}\mu_{\alpha_0}\\ \mu_{\alpha_1}\end{bmatrix}, \begin{bmatrix}\sigma^2_{\alpha_0} & \sigma_{\alpha_0\alpha_1}\\ \sigma_{\alpha_1\alpha_0} & \sigma^2_{\alpha_1}\end{bmatrix}\right)\\
&\text{Level 3:}\\
&\quad \begin{bmatrix}\boldsymbol{\alpha}_{jk}\\ \boldsymbol{\tau}_{jk}\end{bmatrix} \sim N\left(\begin{bmatrix}\boldsymbol{\mu}_\alpha\\ \boldsymbol{\mu}_\tau\end{bmatrix}, \begin{bmatrix}\sigma^2_{\boldsymbol{\alpha}} & \sigma_{\boldsymbol{\alpha\tau}}\\ \sigma_{\boldsymbol{\tau\alpha}} & \sigma^2_{\boldsymbol{\tau}}\end{bmatrix}\right) \text{ with } \boldsymbol{\mu}_\alpha = \begin{bmatrix}\mu_{\alpha_{0j}}\\ \mu_{\alpha_{1j}}\\ \mu_{\alpha_2}\end{bmatrix}; \boldsymbol{\mu}_\tau = \begin{bmatrix}\mu_{\tau_0}\\ \mu_{\tau_1}\\ \mu_{\tau_2}\end{bmatrix}
\end{aligned} \tag{3}$$

Note that for the cross-level interaction among Session and Burst we estimate a fixed effect only (β and λ). For all other effects, we estimate random effects. That is, we estimate individual differences in slopes and variances but also within-person differences among bursts. The vector $\boldsymbol{\mu}_\alpha$ captures the fixed effects of the location part and $\boldsymbol{\mu}_\tau$ captures the fixed effects of the scale part of the model. The random effects are captured in the Level 2 and 3 covariance parameters.

The hyperpriors for the baseline model are defined as

$$\begin{bmatrix} \mu_{\alpha_0} \\ \mu_{\alpha_1} \\ \mu_{\alpha_2} \\ \boldsymbol{\mu}_\tau \\ \beta \\ \lambda \end{bmatrix} \sim N\left(\mathbf{a}, b\mathbf{I}\right)$$

$$\begin{bmatrix} \sigma^2_{\boldsymbol{\alpha}} & \sigma_{\boldsymbol{\alpha\tau}} \\ \sigma_{\boldsymbol{\tau\alpha}} & \sigma^2_{\boldsymbol{\tau}} \end{bmatrix}^{-1} \sim scaled\text{-}Wishart\left(\mathbf{R1}, k1\right)$$

$$\begin{bmatrix} \sigma^2_{\alpha_0} & \sigma_{\alpha_0\alpha_1} \\ \sigma_{\alpha_1\alpha_0} & \sigma^2_{\alpha_1} \end{bmatrix}^{-1} \sim scaled\text{-}Wishart\left(\mathbf{R2}, k2\right)$$

Next, we add Age and DS to obtain the full model age is a between-person predictor and DS is a time-varying predictor which has been measured yearly.

Level 1:

$$\begin{aligned}
y_{ijk} \sim& N(\mu_{ijk}, \sigma^2_{\epsilon_{ijk}}) \\
\mu_{ijk} =& \alpha_{0jk} + \alpha_{1jk}\text{Session}_{ijk} + \alpha_{2jk}\text{Burst}_{jk} + \beta\text{Session}_{ijk}\text{Burst}_{jk} + \\
& a_0\text{Age}_k + a_1\text{Session}_{ijk}\text{Age}_k + a_2\text{Burst}_{jk}\text{Age}_k + \\
& d_0\text{DS}_{jk} + d_1\text{Session}_{ijk}\text{DS}_{jk} + d_2\text{Burst}_{jk}\text{DS}_{jk} \\
log(\sigma^2_{\epsilon_{ijk}}) =& \tau_{0k} + \tau_{1k}\text{Session}_{ijk} + \tau_{2k}\text{Burst}_{ijk} + \lambda\text{Session}_{ijk}\text{Burst}_{jk} + \\
& av_0\text{Age}_k + av_1\text{Session}_{ijk}\text{Age}_k + av_2\text{Burst}_{jk}\text{Age}_k + \\
& dv_0\text{DS}_{jk} + dv_1\text{Session}_{ijk}\text{DS}_{jk} + dv_2\text{Burst}_{jk}\text{DS}_{jk} \\
\begin{bmatrix} \mathbf{a} \\ \mathbf{b} \\ \mathbf{av} \\ \mathbf{bv} \end{bmatrix} \sim& N\left(\mathbf{a}, b\mathbf{I}\right)
\end{aligned}$$

In both location and scale parts, age and DS are used as predictors. This is not a requirement and one may introduce predictors at the location or scale part of the model only.

2.4 Model Estimation

All Bayesian hierarchical models described earlier were estimated using MCMC simulations. The priors were uninformative and all parameters in the models converged with potential scale reduction factors $\hat{R} < 1.1$. Convergence was achieved within 70,000 iterations, of which 20,000 were used as burn-in Statistical significance was determined using 95% credibility intervals (C.I.).

All models were specified in R (R Core Team, 2013) using the R2jags package (Su and Yajima, 2013) to call the Gibbs sampler JAGS (Plummer, 2013) which can be considered as a Unix version of openBUGS.

Table 1: Fixed effects estimates of the location.

	Estimate	95% C.I.	$\hat{R}$
α_0	**7.152**	[6.58 ; 7.77]	1.00
α_1	-0.095	[-0.77 ; 0.57]	1.00
α_2	**-0.125**	[-0.14 ; -0.11]	1.00
β	**0.018**	[0.01 ; 0.02]	1.01
a_0	**0.030**	[0.02 ; 0.04]	1.05
a_1	**0.000**	[0.00 ; 0.00]	1.01
a_2	**0.002**	[0.00 ; 0.00]	1.01
d_0	-0.006	[-0.01 ; 0.00]	1.01
d_1	**0.000**	[0.00 ; 0.00]	1.00
d_2	**0.002**	[0.00 ; 0.00]	1.01

Table 2: Fixed effects estimates of the scale

	Estimate	95% C.I.	95% C.I.
τ_0	**-1.807**	[-1.89 ; -1.72]	1.01
τ_1	**-0.103**	[-0.15 ; -0.06]	1.01
τ_2	**-0.101**	[-0.15 ; -0.06]	1.01
λ	**0.038**	[0.02 ; 0.06]	1.02
av_0	-0.008	[-0.02 ; 0.01]	1.00
av_1	**0.004**	[0.00 ; 0.01]	1.00
av_2	0.001	[-0.01 ; 0.01]	1.01
dv_0	-0.002	[-0.01 ; 0.01]	1.00
dv_1	**0.001**	[0.00 ; 0.00]	1.00
dv_2	**0.000**	[0.00 ; 0.00]	1.01

3. Results

In Table 1 we report the location fixed effects estimates. All estimates represent posterior means and values that do not contain zero in their C.I. are considered statistically significant and are reported in bold. The burst-slope is negative indicating that the average reaction time decreased across years (α_2) but not across sessions (α). The effects on the location associated to Age are in the a_0 to a_2 estimates and the effects of DS are reported in the d_0 to d_2 estimates. For example, higher vales in DS were associated to slower decreases in RT across the four burst (d_2) and higher age also increased the average RT estimate at study entry (a_0).

Figure 1 shows the predicted individual estimates of RT. All values are transformed back from the log-scale into the original ms metric.

The posterior means of the scale part of the model are reported in Table 2. Note that the estimates are on the natural log scale. The fixed effects of τ_1 and τ_2 indicate that the within-person variability decreased on average both across and within bursts. Age had a dampening effect (av_1) on the within-persons change rate across sessions in the sense that older adults decreased variability at slower rates compared to younger adults. The effect of DS was similar indicating that higher DS values decreased the rate of change in variability across bursts.

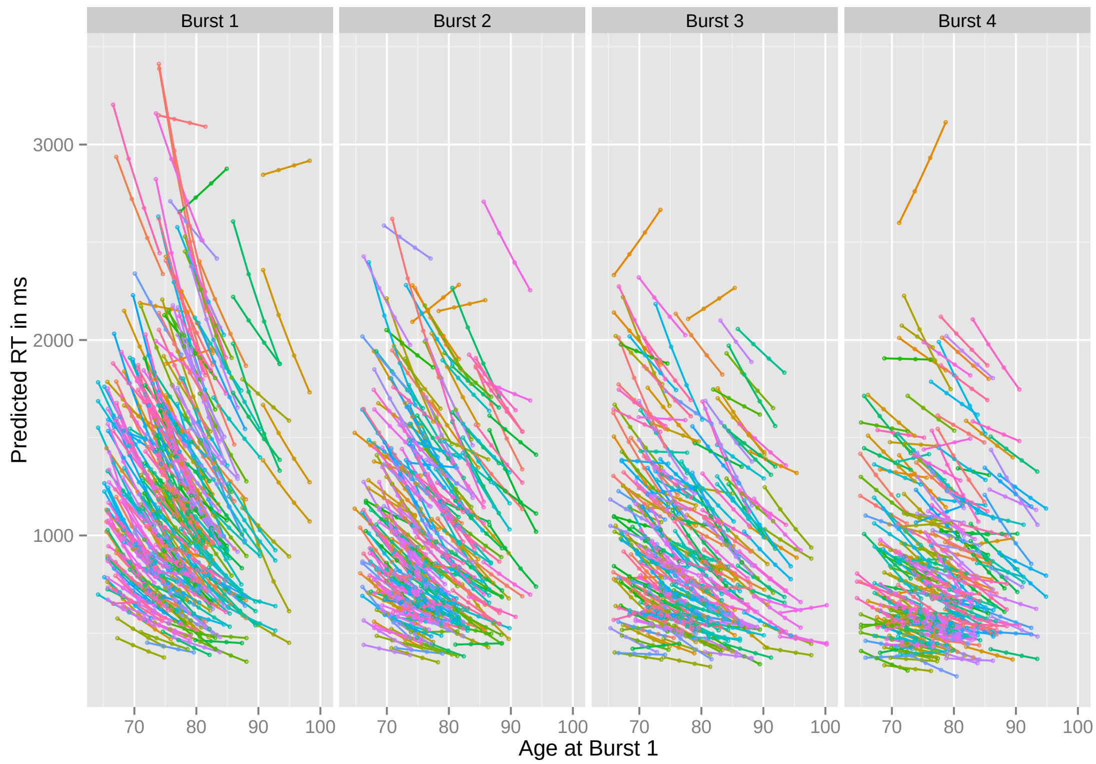

Figure 1: Predicted individual reaction times.

Table 3: Random effect estimates across the location and the scale

	1	2	3	4	5	6
1. α_0	**0.36**					
2. α_1	-.12	**0.08**				
3. α_2	-.13	**.14**	**0.10**			
4. τ_0	**-.55**	.08	.08	**.41**		
5. τ_1	**.26**	-.11	-.07	**-.40**	**0.16**	
6. τ_2	**.31**	-.07	-.14	**-.52**	.07	**0.20**

Note. Variances in diagonal

Figure 2 shows trajectories of individual SD across sessions and bursts separated by the age at study entry.

The random effects estimates across the location and the scale are reported in Table 3 and show individual differences on the diagonal. Off-diagonal elements report the correlations among the random effects. The location parameters are denoted with α's and the scale parameters are denoted with τ's. All parameters showed significant variability indicating individual differences in the initial RT score, in changes across time, in the average individual variability and in changes across time in within-person variability. The correlations among the location intercept random effect α_0 and the three τ parameters capture relevant associations among the random effects of the location and scale part of the model.

In a three level model we can not only estimate random effects between-persons at level 3 but also within-persons but between-bursts at level 2. Here, both random effects and indicated considerable variability in the intercept $\alpha_{0j} = 0.57$ and the slope parameter $\alpha_{1j} = 0.63$ showing that the intercepts among bursts differed and

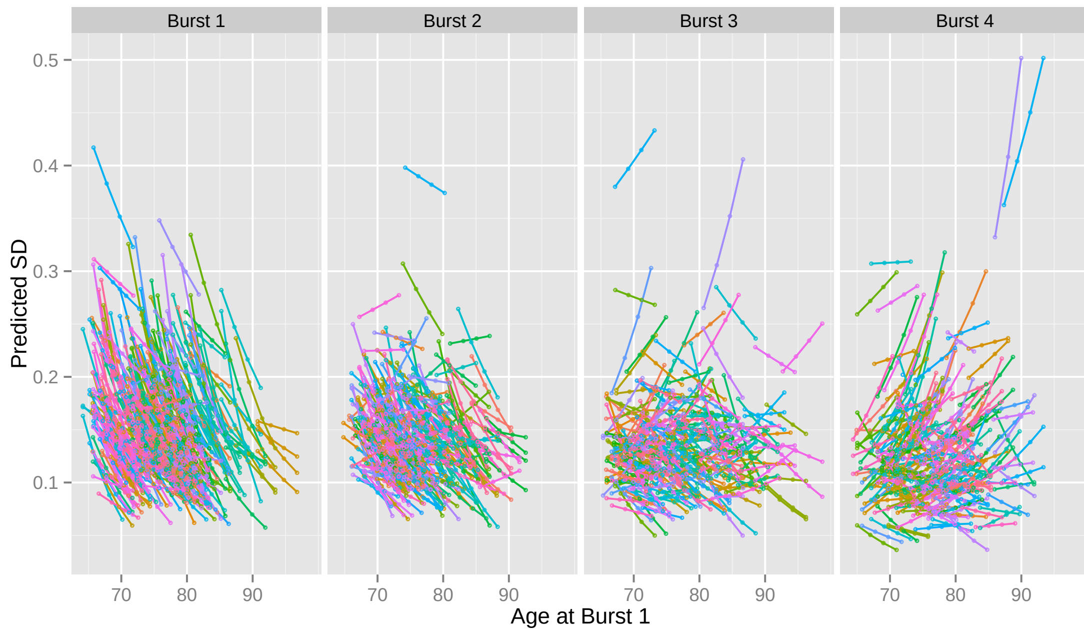

Figure 2: Predicted individual SD on the log scale across all four burst and four sessions.

Table 4: Between bursts and with-person random effects.

	1	2
1. α_{0j}	**0.57**	
2. α_{1j}	-.17	**0.63**

also changes in the session slopes among burst differed widely. Note that we only estimated between-burst random effects for the location part of the model.

4. Discussion

In recent years research on within-person variability has been intensified and results suggest that residual variability is not merely a nuisance parameter but can still carry valuable information. The estimation and interpretation of within-person variability can be approached from multiple perspectives. Here we used a recently developed mixed effects location scale model (LSM; Hedeker and Mermelstein, 2007) and extended it to a 3-level situation making use of a Bayesian modeling framework. This model has the advantage that it estimates all parameters simultaneously and maintains the dependency among the location and scale parameters. Predictors can be included within- and/or between-person level to model the location and scale part. However, research on within-person variability also puts additional requirements on the data. The reliable estimation of variance components requires more frequent measurements and, in order to make predictions about short-term variation and longer term changes the design of studies need to be adapted accordingly. For example, the investigation of the predictive value of within-person variability in long-term changes in cognitive data can only be examined with a study design that allows the separation of different timescale. The measurement burst design Nesselroade (1991) affords this possibility and provides information about changes on two different time scales. At the same time it also introduces at least one additional level of analysis which complicates the estimation of this type of models.

The purpose of this work was to present an extension of the mixed effects LSM to three level data. The possibilities offered by this model are numerous and here we only presented a basic model with two predictor variables to explore changes in covariances in the location and the scale parameters. More predictors can be included, however, the complexity of the model increases quickly to a degree which makes the estimation in a reasonable amount of time difficult.

Nonetheless, the current application demonstrated how the LSM can be used in multilevel data. In the present application we found large and reliable individual differences in all parameters of the location and scale as well as among the location parameters within participants. Not only did we see changes in the average RT but also changes across time in the variance. Important to note are the significant correlations at the person level which indicate that the location and scale parameters are not independent. Notably, initial within-person variability was negatively associated to changes in variability across weeks and years. These findings indicate that participants with larger initial variability decreased faster compared to participants with smaller initial variability. In this demonstration, no evidence was found that within-person variability is associated to long term changes in average RT performance.

In all, the mixed effects LSM has demonstrated its potential and a number of extensions of this model are imaginable such as the inclusion of autoregressive error structures (cf. Wang et al., 2012) or the extension to the multivariate space.

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