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Advancing Occupational Stress and Health Research and Interventions Using Latent Difference Score Modeling

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Occupational stress theories are rooted in the dynamic nature of the stress process, but few researchers examine intraindividual changes in the stress and well-being process. Analyses of intraindividual change over time enable researchers to evaluate theoretical propositions and build models that may be misspecified by cross-sectional data. We introduce a longitudinal data analysis method that can be used to advance stress theories and more accurately evaluate current organizational interventions. Specifically, latent difference score (LDS; J. J. McArdle, 2001, A latent difference score approach to longitudinal dynamic structural analysis. In R. Cudek, S. DuToit, & D. Sörbom, Eds., Structural equation modeling: Present and future*, pp. 342–380, Lincolnwood, IL: Scientific Software International) modeling has recently emerged as a versatile tool for investigating intraindividual change in measured variables in clinical and developmental research (C. D. Kouros & E. M. Cummings, 2010, Longitudinal associations between husbands' and wives' depressive symptoms,* Journal of Marriage and Family*, Vol. 72, pp. 135–147; I. Schindler, U. M. Staudinger, & J. R. Nesselroade, 2006, Development and structural dynamics of personal life investment in old age,* Psychology and Aging*, Vol. 21, pp. 737–753). Organizational or occupational health researchers, however, have yet to take advantage of the LDS approach. We discuss potential implications for the LDS approach in evaluating organizational interventions and stress theories and*

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provide a didactic illustration of LDS modeling using data from the National Longitudinal Survey of Youth.

Keywords: latent difference score modeling, longitudinal, change, stress

The theoretical underpinnings of many organizational phenomena are rooted in the concept of intraindividual change over time, and there has been a general shift away from static relationships to focusing on how variables relate over time (Pitariu & Ployhart, 2010). For example, organizational stress researchers have recently examined the day-to-day recovery process of employees (Demerouti, Bakker, Sonnentag, & Fullagar, 2012) and within-person fluctuations of proactive behavior (Fay & Sonnentag, 2012). Analyses of change over time enable researchers to evaluate theoretical propositions and build models that may be misspecified by cross-sectional data. In other words, the inclusion of time enables researchers to more accurately infer causality. Inferring causality requires demonstrating that three conditions are met: (1) The cause and effect are related, (2) the cause precedes the effect in time, and (3) other competing explanations for the observed effect can be ruled out (Popper, 1959). The second condition can never be met with cross-sectional data.

This shift to examining longitudinal relationships has corresponded with an increased interest in statistical methods for modeling intraindividual change and assessing interindividual differences in intraindividual change. For example, a number of organizational studies have applied latent growth modeling (LGM) or random coefficient modeling growth curve models to test hypotheses about intraindividual change (e.g., Bentein, Vandenberg, Vandenberghe, & Stinglhamber, 2005; Chan & Schmitt, 2000; Eschleman, Alarcon, Lyons, Stokes, & Schneider, 2012; Ployhart, Holtz, & Bliese, 2002). Although there are many positive aspects of these approaches, they can be somewhat limited in the types of research questions they can address. Neither method is able to consider autoregressive effects in which the intraindividual changes in a variable over time may be a function of the level of that variable at the previous time point. For example, we may expect less intraindividual change in work stress for those with higher preexisting levels of work stress compared with those who have lower preexisting levels. In addition, both LGM and random coefficient modeling growth models consider constant intraindividual change. This is intraindividual change that occurs consistently across time points and is not influenced by the previous level of the variable. Nonlinear intraindividual change can be modeled by adding quadratic and cubic time functions, but these functions are still not capable of modeling more dynamic intraindividual change.

Recently, an alternative structural equation modeling (SEM) approach has been developed by McArdle and colleagues (McArdle, 2001, 2009; McArdle & Hamagami, 2001). The approach is based on modeling latent difference scores (LDSs) and combines parts of the cross-lag and latent trajectory models. It has been proposed as a general framework for the study of intraindividual change (McArdle, 2009; Ferrer & McArdle, 2003, 2010). In its full form, it provides for both proportional intraindividual change relative to the previous time point and constant intraindividual change across time points. The LDS approach offers several advantages. One major advantage is that it can specify a dual-change model that includes both intraindividual changes proportional to the previous time point and constant intraindividual change. As such, it is capable of modeling correctly the intraindividual change for a variable. The combinations of autoregressive effects and constant intraindividual change allow for a wide variety of possible patterns of intraindividual change. For example, it allows for there to be greater intraindividual change between some time points than others. Another advantage is that it models intraindividual change scores between two time points that can serve as outcomes to be predicted by other variables. These models have been used to study a number of topics. For example, LDS models have been used to study relationships between husbands' and wives' depressive symptoms (Kouros & Cummings, 2010), personal life span investment (Schindler, Staudinger, & Nesselroade, 2006), perfection and depression (Hawley, Ringo Ho, Zuroff, & Blatt, 2006), and sleep and mood (Sbarra & Allen, 2009). However, to our knowledge, they have not been used in occupational stress and health research.

In the present study, we describe the LDS approach and contrast it with LGM and the autoregressive latent trajectory (ALT) model. The ALT model is also designed to capture autoregressive and constant intraindividual change, and was recently introduced to organizational researchers (Zyphur, Chaturvedi, & Arvey, 2008). We consider an empirical example using ratings of job demands (i.e., work safety perception) and job satisfaction. In addition, we show how LDS models can be applied to address a number of research questions concerning the nature of internal change for these variables and how they influence each other over time. Before describing LDS models, we provide a brief treatment of the LGM and ALT approaches to assessing intraindividual change.

LGM

To capture intraindividual change, the LGM approach (Meredith & Tisak, 1990) models a trajectory of change along each of the focal constructs for individuals across time while incorporating each individual's initial status. The LGM approach requires that the constructs be measured over at least three time points. Each time point has a separate loading on two latent factors: intercept and linear intraindividual change. Thus, systematic intraindividual change can be evaluated by the mean slope latent factor. In addition, interindividual variability in linear change can be predicted by either the intercept latent factor or a third variable. The intercept factor in an LGM has fixed loadings of 1 for each time point. To evaluate linear intraindividual change across equal time intervals, the slope factor generally has fixed loadings of 0 at Time 1, with the fixed loadings increasing by 1 for each subsequent time point (e.g., Time 1 = 0, Time 2 = 1, Time 3 = 2, Time 4 = 3). Nonlinear, or quadratic, intraindividual change can also be estimated by adding a third latent factor. The quadratic intraindividual change factor includes fixed factor loadings, which are estimated by squaring the linear intraindividual change factor loading for each time point (e.g., Time 1 = 0, Time 2 = 1, Time 3 = 4, Time 4 = 9). An advantage of the LGM approach is that the model can be adapted to evaluate intraindividual change using unequal time intervals (see Duncan, Duncan, Strycker, Li, & Alpert, 1999). However, the LGM approach is limited in that autoregressive effects are not included during model specification.

ALT

ALT models (Bollen & Curran, 2004; Curran & Bollen, 2001) incorporate autoregressive effects into the basic LGM. Essentially, each score is regressed onto the intercept and slope latent variables as in the LGM. In addition, each score is regressed onto the score of the previous time point. Thus, the model contains both an overall intraindividual change measured by the slope latent variable and autoregressive effects measured by the regression coefficients between consecutive time points. It is common to constrain the autoregressive effects to be equal across the time series. Detailed descriptions of the ALT model are presented in Curran and Bollen (2001) and Bollen and Curran (2004).

One issue with specifying ALT models is the treatment of the score for the first time point. Bollen and Curran (2004) describe two options. One is to treat the first time point's score as predetermined. This is accomplished by not having the score load on the intercept and slope factors, but still specify it as predicting the score at the second time point. The second option is to estimate the loadings for the first time point on the intercept and slope factors. The estimated loadings are a function of the autoregressive parameter (ρ). The loading on the intercept ($\lambda_{1\alpha}$) is calculated using the following formula:

$$\lambda_{1\alpha} = \frac{1}{1-\rho}. \tag{1}$$

The loading on the slope ($\lambda_{1\beta}$) equals

$$\lambda_{1\beta} = -\left(\frac{\rho}{(1-\rho)^2}\right). \tag{2}$$

Both options have advantages and disadvantages. Treating the first score as predetermined avoids the necessity of using nonlinear constraints, which can lead to estimation problems. However, this approach does not include the score at the first time point when estimating the intercept and slope factors. In contrast, the nonlinear constraints approach does consider the first time point in estimating the intercept and slope factors.

UNIVARIATE LDS MODELS

Figure 1 portrays a path diagram for a univariate LDS model of job satisfaction at four time points. In the diagram, $JSAT_0$ to $JSAT_3$ represent the observed scale scores for job satisfaction at each time point. The "e"s represent measurement error, and $jsat_0$ to $jsat_3$ represent true score job satisfaction for the respective time points. LDS_1 refers to the LDS for the difference between job satisfaction at Times 1 and 2. It is important to note that this difference score is latent. For example, the variance in job satisfaction at Time 1 ($JSAT_0$) has been partitioned into true score ($jsat_0$) and

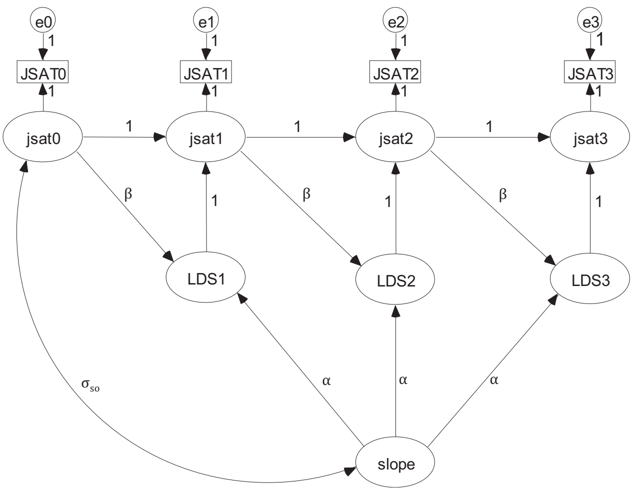

Figure 1. Path diagram for univariate latent difference score (LDS) model for job satisfaction. $JSAT_0$ to $JSAT_3$ = observed scale scores for job satisfaction at each time point; e = measurement error; $jsat_0$ to $jsat_3$ = true score job satisfaction for the respective time points.

measurement error variance (e_0). Thus, some of the concerns about the unreliability of difference scores do not apply to these models (King et al., 2006). The model incorporates autoregressive intraindividual change through the parameters labeled β. These reflect the influence of the preceding time point on the LDS. The latent variable slope measures constant intraindividual change and is defined by its effects (α) on each of the LDSs. The αs are constant intraindividual change coefficients and are typically, but not necessarily, fixed to a value of 1. If the time points are not equal intervals, then different constraints can be placed on the model to reflect this. This is a dual-change model because it incorporates both autoregressive (β) and constant (α) intraindividual change.

Although the model in Figure 1 appears complicated, there are very few parameters that are estimated. This is because of the number of constraints typically employed in the LDS models. For example, the autoregressive effects and measurement error variances are typically constrained to be equal across time points. If these constraints are placed on the model in Figure 1, only seven parameters are freely estimated: one autoregressive effect value, three variances (common error, slope, and intercept), two means (slope and intercept), and one correlation between the slope and intercept.

The result of the dual-change model is that an LDS is expressed as a function of both autoregressive and constant intraindividual change. For example, the LDSs in Figure 1 can be defined as

$$LDS_1 = \beta(jsat_0) + 1.00slope, \tag{3}$$

$$LDS_2 = \beta(jsat_1) + 1.00slope, \tag{4}$$

$$LDS_3 = \beta(jsat_2) + 1.00slope. \tag{5}$$

These equations reveal the dual-change nature of the LDSs. Although they appear to be somewhat simple, the series of LDSs can capture dynamic intraindividual changes in a variable. For example, it is possible for some LDSs to be positive and some to be negative within a time series.

Possible Univariate Research Questions

Univariate LDS models can address a number of interesting research questions that autoregressive analyses and LGM cannot. The primary research question for univariate models is what the best model of intraindividual change is. This includes specific questions about what sources of intraindividual change are present and what the nature of those intraindividual changes is. Our first possible research question is whether or not dual change is present. To test this, a proportional change score model can be tested by freeing the autoregressive effects and omitting the constant intraindividual change slope. A constant change score model can be estimated by fixing the autoregressive effects to zero and freeing the slope mean and variance. Finally, the dual-change model can be estimated and tested against the other two models. The model comparisons test hypotheses about the nature of intraindividual change. For example, comparing the dual-change model with the proportional change model tests whether or not constant intraindividual change is needed. Similarly, comparing the dual-change model against the constant change score model tests for the presence of significant autoregressive effects.

Another research question concerns what the nature of the present sources of intraindividual change is. LDS models are capable of modeling a number of different patterns of intraindividual change. The specific pattern depends on the nature of autoregressive effects and constant intraindividual slope means. For example, it may be that higher levels of job satisfaction are associated with less intraindividual change at the next time point than lower levels. Another possibility is that lower levels of job satisfaction may lead to increases in job satisfaction at the next time point whereas higher levels may lead to decreases. These two examples represent the nature of the autoregressive effects. In addition, it may be that job satisfaction has constant positive intraindividual change overtime, which describes the nature of the constant intraindividual slope.

A third research question concerns where the greatest autoregressive intraindividual changes occur. In the present context, we may be interested in examining whether prior levels of job satisfaction affect intraindividual change across all time points. This information can be obtained when the equality constraints placed on the autoregressive parameters are removed and the parameters are evaluated separately. For example, it may be that prior levels of job satisfaction have a greater effect on intraindividual changes in job satisfaction when employees are faced with a career decision or promotional opportunities. In other words, greater autoregressive effects may be present when employees have to make cognitive evaluations of how much they like their jobs. Researchers examining intraindividual change in stress or health within a workday or workweek (e.g., Fritz & Sonnentag, 2009) may also find the univariate LDS model fruitful. It may be that prior levels of need for recovery have a greater effect on intraindividual changes in need for recovery at different points during the workweek.

Another research question addresses where the greatest accumulative intraindividual changes (autoregressive and constant change) occur. It is possible to compare the LDSs to assess differences in intraindividual change across time. For example, we may hypothesize that the most intraindividual change occurs at the beginning of one's career. Or, in regards to stress interventions, an organization is likely to be interested in when the greatest intraindividual change in well-being occurs and when the intraindividual change in well-being stops. We could compare the first LDS against the second LDS to test this hypothesis. To accomplish this, we would obtain model-implied factor scores from our analysis and compare them using a paired samples *t* test. In sum, the inclusion of both autoregressive and constant intraindividual change parameters in univariate LDS models enables researchers to test several potentially theoretical questions.

Finally, the latent change scores can serve as predictors or outcomes of external variables. For example, it may be that older workers experience less intraindividual change in job satisfaction compared with younger workers. Such hypotheses can be tested by specifying age as a predictor of the LDS. An analogous hypothesis could be tested using personality or other time-invariant predictors. Similarly, the LDS could be used to predict organizational outcomes. For example, greater intraindividual change in job satisfaction may be associated with retirement age. In addition, it may be that intraindividual change in job satisfaction later in one's career is more important in predicting retirement age than change in job satisfaction earlier in one's career. Similar research questions can be posed to examine daily stressors and recovery of employees. For example, increases in need for recovery at the beginning of the workweek may be less likely to precede weekend recovery strategies compared with increases in need for recovery at the end of the workweek. Specifying the LDS as a predictor of a subsequent time-invariant variable can test such hypotheses.

Empirical Example

In the following example, we conducted a series of univariate LDS models using Mplus 5.1 (Muthén & Muthén, 2008) to address several of the aforementioned research questions associated with univariate LDS models. Examples of annotated Mplus syntax for LDS models are presented in a technical appendix for Sbarra and Allen (2009). It is important to note that these analyses can be conducted with any standard SEM software program. Our major goal was to demonstrate how these analyses can be conducted and how the various types of research questions can be addressed.

The data for this example came from the National Longitudinal Survey of Youth (NLSY; Center for Human Resource Research, 1995). The NLSY is a nationally representative sample of 12,686 American young men and women who were between 14 and 22 years of age at the onset of the study in 1979. Questions pertained to a wide range of topics, including environmental characteristics, family life, work life, and physical health. In addition, data from the NLSY have been used in several published studies to examine organizational behaviors and attitudes (Currie & Fallick, 1996; Trevor, 2001; Wilk & Sackett, 1996). We included data from respondents who completed measures of job satisfaction and job safety annually from 1979 to 1982 and were employed at the time of data collection. The job satisfaction and job safety variables were selected because the data represented a bivariate dual-change model for both variables, which enables the didactic example to be the most comprehensive. The sample used (N = 2,381) was an average age of 20 years old at the onset of the study, 43% female, 13% Hispanic, 19% African American, and 68% were neither Hispanic or African American.

Job satisfaction was assessed with eight items measuring satisfaction with various aspects of their jobs: supervisor, promotion opportunities, job security, job autonomy, surroundings, experience, income, and coworkers. The reliability of this scale ranged from .71 to .75 across the four time points. Each item was assessed on a 4-point Likert scale ranging from 1 (*not true at all*) to 4 (*very true*).

Work safety perceptions were assessed with two items: "You are exposed to unhealthy work conditions" and "The job is dangerous." The reliability of this scale ranged from .79 to .86 across the four time points. As with job satisfaction, each item was assessed on a 4-point Likert scale ranging from 1 (*not true at all*) to 4 (*very true*).

LDS Analyses

What Is the Best Model of Intraindividual Change?

Table 1 presents the means, standard deviations, and correlations among the study variables. We estimated a series of LDS models to determine the best-fitting model of intraindividual change for job satisfaction. The results of the models are presented in Table 2. We first estimated the dual-change

Table 1. Means, Standard Deviations, and Correlations Among Study Variables

Variable	Mean	*SD*	1	2	3	4	5	6	7	8
1. Job satisfaction Time 0	3.08	0.51								
2. Job satisfaction Time 1	3.16	0.49	.40							
3. Job satisfaction Time 2	3.16	0.50	.31	.44						
4. Job satisfaction Time 3	3.19	0.49	.31	.35	.47					
5. Work safety Time 0	1.92	0.88	−.15	−.12	−.15	−.13				
6. Work safety Time 1	1.90	0.88	−.11	−.19	−.18	−.13	.51			
7. Work safety Time 2	1.92	0.90	−.08	−.13	−.21	−.16	.48	.60		
8. Work safety Time 3	1.95	0.90	−.08	−.13	−.17	−.18	.44	.53	.64	
9. Age (years)	20.19	1.52	.02	.00	.00	.02	.13	.08	.05	.06

Note. N = 2,381. Correlations greater than ±.04 are significant at $p < .05$.

Table 2. Univariate Change Score Models for Job Satisfaction

Parameter and fit index	Dual-change score	Proportional change score	Constant change score
Autoregressive coefficient (β)	−0.56*	0.01*	0.00[a]
Constant change coefficient (α)	1.00[a]	0.00[a]	1.00[a]
Intercept mean (μ_o)	3.08*	3.10*	3.10*
Slope mean (μ_s)	1.80*	0.00[a]	0.03*
Intercept variance (σ_o)	0.13*	0.09*	0.12*
Slope variance (σ_s)	0.04*	0.00[a]	0.01*
Correlation ($\rho_{o,s}$)	.58*	.00[a]	−.40*
Error variance (Ψ)	0.14*	0.16*	0.14*
Parameters	7	4	6
Degrees of freedom (*df*)	7	10	8
Chi square (χ^2)	48.49*	145.55*	81.15*
CFI	.98	.92	.96
SRMR	.07	.10	.09
Compared with proportional change score	$\Delta\ \chi^2(3) = 98.06^*$		
Compared with constant change score	$\Delta\ \chi^2(1) = 32.66^*$		

Note. CFI = comparative fit index; SRMR = standardized root mean residual.
[a] Fixed parameter.
* $p < .05$.

model. The autoregressive effects were constrained to be equal across time. In addition, we constrained the error variances to be equal across time. The model had acceptable fit, $\chi^2(7) = 48.49$, $p < .01$; comparative fit index (CFI) = .98; standardized root mean residual (SRMR) = .07. In addition, the autoregressive effects and slope means were statistically significant, indicating that both sources of intraindividual change were present. We compared the fit of this model against the proportional change model in which there were only autoregressive effects and no constant intraindividual change. The dual-change model fit significantly better, $\chi^2_{\text{dif}}(3) = 98.06$, $p < .01$, suggesting that constant intraindividual change was necessary. Similarly, the dual-change model fit better than the constant change score model in which there were no autoregressive effects, $\chi^2_{\text{dif}}(1) = 32.66$, $p < .01$, indicating that autoregressive effects were necessary. We also estimated a model in which the error variances were allowed to vary. This model did not fit significantly better than the simpler model in which the error variances were constrained, $\chi^2_{\text{dif}}(3) = 3.87$, $p = .28$. Finally, we also examined whether or not the autoregressive effects varied across time. To test this, we freed the autoregressive parameters. This model did fit the data significantly better than the simpler constrained model, $\chi^2_{\text{dif}}(2) = 10.13$, $p < .01$. However, the unstandardized autoregressive parameter estimates ranged from −0.51 to −0.52, suggesting that the differences, although statistically significant, were not large. Thus, the dual-change model with freed autoregressive effects and constrained error variances was the best-fitting model.

There are several effects that may be of interest to occupational stress and health researchers. First, the initial mean and deviation can be used to describe participants' initial standing on a variable. In this case, the average individual began the study with some level of job satisfaction, but the amount varied between participants. Second, the slope mean and deviation are used to evaluate constant intraindividual change. In the present example, participants generally increased in job satisfaction irrespective of their previous standing. However, the significant slope deviation indicates that the rate of constant intraindividual change varied between participants.

How Do Previous Levels Affect Intraindividual Change?

The significant negative autoregressive coefficient indicates that intraindividual change in job satisfaction is partially dependent on a participant's previous standing on job satisfaction. More specifically, the negative autoregressive coefficient indicates that greater job satisfaction leads to less intraindividual growth in job satisfaction. Thus, the LDS at each time point is a function of both previous standing and constant change. We can illustrate these findings by writing three regression equations using the autoregressive coefficients and the slope, one for each of the three LDSs:

$$\mathrm{LDS}_1 = -0.51(\mathrm{jsat}_0) + 1.00(1.64), \tag{6}$$

$$\mathrm{LDS}_2 = -0.52(\mathrm{jsat}_1) + 1.00(1.64), \tag{7}$$

$$\mathrm{LDS}_3 = -0.51(\mathrm{jsat}_2) + 1.00(1.64). \tag{8}$$

It can be informative to plug various values for the job satisfaction scores into the LDS equation. For example, an individual with a true score for jsat_0 of 2 would have an expected initial LDS of $-0.51(2) + 1.00(1.64) = 0.62$. Thus, we would expect an increase in job satisfaction rating for Time 2. In contrast, someone with a jsat_0 score of 3.5 would have an initial LDS of -0.15. We would expect a slight negative change in this person's score at Time 2. This suggests that those lower in initial job satisfaction at the first time point will see their scores increase at a greater rate for Time 2 than those with higher initial job satisfaction. Figure 2 displays the model-implied values across a range of values for job satisfaction.

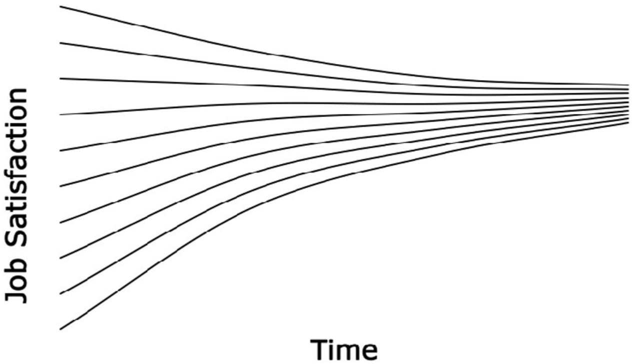

Figure 2. Univariate latent difference score model implied job satisfaction.

Where Do the Greatest Autoregressive Changes Occur?

To examine where the greatest proportional intraindividual changes occur, we need to establish that the autoregressive effects varied across time. This is tested by freeing the autoregressive parameters (β) and comparing that against the model in which these parameters are constrained to be equal. As mentioned above, the free autoregressive parameter model did fit the data significantly better than the simpler constrained model, $\chi^2_{dif}(2) = 10.13$, $p < .13$. In addition, the unstandardized autoregressive parameter estimates ranged from −0.52 to −0.51. The biggest effect was that the autoregressive effect was largest at Time 2, affecting change at Time 3. This suggests that the autoregressive effects did differ across time, although the difference appeared to be small.

Where Do the Greatest Intraindividual Changes Occur?

Researchers are often concerned with determining where the greatest intraindividual changes in a variable occur. For example, referring to Figure 2, the biggest intraindividual change appeared to occur between the first and second time points.[1] To test this, we compared the model-based LDSs extracted from Mplus using paired samples *t* tests. Interestingly, the mean for the LDSs between Times 2 and 3 was negative, suggesting a slight negative intraindividual change. To compare the LDSs, we used the absolute value of the mean for the second LDS. The first LDS mean ($M = 0.08$, $SD = 0.09$)

[1] It is important to note that the model-implied values graphed in Figure 2 also appear to show that the greatest between-persons variability in intraindividual change occurred between the first and second time points.

was significantly higher than the absolute value of the second LDS mean (M = 0.01, SD = 0.05), $t(2380) = 27.42$, $p < .01$, and third LDS mean (M = 0.03, SD = 0.02), $t(2380) = 33.93$, $p < .01$. The second LDS mean was significantly lower than the third, $t(2380) = -20.69$, $p < .01$. This suggests that the greatest intraindividual change occurred between Times 1 and 2, and that the intraindividual change between Times 3 and 4 was greater than the intraindividual change between Times 2 and 3.

Do External Variables Predict Intraindividual Change?

To assess whether age predicted intraindividual changes in job satisfaction, we regressed each of the LDSs onto the initial age of participants. The resulting model fit the data reasonably well, $\chi^2(5) = 30.98$, $p < .01$; CFI = .99; SRMR = .02. However, age was not significantly related to any of the LDSs. All three unstandardized regression coefficients were zero. Thus, it does not appear that intraindividual changes in job satisfaction relate to age in our sample.

BIVARIATE LDS MODELS

It is possible to estimate bivariate LDS models to examine changes in two variables by combining the univariate models for two variables. In addition to the information provided by the univariate LDS models, bivariate models can assess how intraindividual changes in one variable are related to the previous standing of the other variable. For example, we consider a bivariate model with job satisfaction and work safety perceptions. Figure 3 presents the path diagram for this model. The diagram essentially depicts one dual-change model for job satisfaction and one for work safety perceptions. All of the terms and variables are defined as before. The two models are combined by allowing the initial means and slopes to covary across variables. In addition, coupling parameters (γ) exist between the levels of each variable and the subsequent LDS of the other variable. That is, job satisfaction at Time 1 leads to intraindividual changes in work safety perceptions at Time 2 (and vice versa). These coupling coefficients allow researchers to test hypotheses about the direction of influence between two variables. For example, it may be that job satisfaction leads to intraindividual changes in work safety perceptions, but work safety perceptions do not lead to intraindividual changes in job satisfaction. Bidirectional relationships are also possible. Although it is common to specify the coupling coefficients for predicting intraindividual change in a variable using the level of the other variable, it

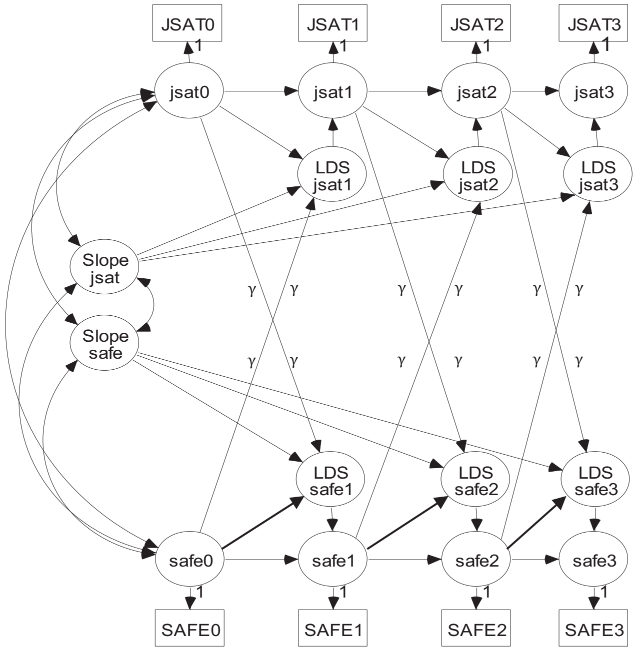

Figure 3. Path diagram for bivariate latent difference score (LDS) model for job satisfaction and work safety perceptions. $JSAT_0$ to $JSAT_3$ = observed scale scores for job satisfaction at each time point; $jsat_0$ to $jsat_3$ = true score job satisfaction for the respective time points; $SAFE_0$ to $SAFE_3$ = observed scale scores for work safety perception at each time point; $safe_0$ to $safe_3$ = true score work safety perception for the respective time points.

also possible to specify direct relationships between LDSs. That is, it is possible to test whether or not intraindividual changes in job satisfaction predict intraindividual changes in work safety perceptions. Thus, bivariate LDS models can be a very powerful tool in examining intraindividual relationships between variables over time.

Possible Bivariate Research Questions

Results from bivariate LDS models can be used to address several interesting research questions. For example, the correlation between intercepts indicates how the initial levels of both variables relate to each other. The correlations between the intercepts and slopes indicate how initial levels of one variable relate to the constant intraindividual change of both variables. For example, a bivariate LDS model with job satisfaction and work safety perceptions would allow us to see whether initial levels of job satisfaction are related to greater constant intraindividual change in job satisfaction and work safety perceptions. We can also test for a relationship between the two constant intraindividual change slopes to examine how constant intraindividual change in work safety perceptions relates to constant intraindividual change in job satisfaction. Similar results can be obtained from the LGM and ALT models; however, the results may differ because of model differences about the assumptions of intraindividual change.

A second research question concerns the autoregressive effects for each variable. In the bivariate model, they now statistically control for the level of the other variable at the previous time point. That is, the autoregressive effects for job satisfaction would control for the level of work safety perceptions at the previous time point. This can help tease apart whether or not the autoregressive effects are spurious. For example, it may be that the autoregressive effects we found for job satisfaction disappear when we consider the level of work safety perceptions at the previous time point. This may indicate that the autoregressive effects were observed because of shared variance between work job satisfaction and work safety perceptions.

Finally, perhaps the most interesting bivariate LDS research questions concern the coupling coefficients. These indicate how intraindividual changes in one variable are predicted by the levels of the other variable at the previous time point. They can be used to help establish whether the relationship between the two variables is unidirectional or bidirectional. Bivariate LDS models provide tests for these possibilities. A slight variation of this would be to specify relationships between the LDS between variables. That is, we could test whether changes in job satisfaction lead to intraindividual changes in work safety perceptions (or vice versa). This feature is exclusive to the LDS approach because the LGM and ALT models do not directly model difference scores.

Empirical Example

We used the same data described above. Prior to conducting the bivariate analyses, we estimated a univariate dual-change model with constrained autoregressive effects for work safety perceptions (see Table 3). In general, the results for work safety perceptions were similar to those for job satisfaction. The model had acceptable fit, $\chi^2(7) = 45.96$, $p < .01$; CFI = .99; SRMR = .03. In addition, the dual-change model fit significantly better than the proportional change score, $\chi^2_{\text{dif}}(3) = 143.76$, $p < .01$, and constant change score models, $\chi^2_{\text{dif}}(1) = 24.71$, $p < .01$. Freeing the autoregressive parameters did not improve model fit, $\chi^2_{\text{dif}}(2) = 3.15$, $p = .21$, but freeing the error variances did, $\chi^2_{\text{dif}}(3) = 17.60$, $p < .01$. Thus, the dual-change model with constrained autoregressive effects and free error variances was the best-fitting model.

Table 3. Univariate Change Score Models for Work Safety Perceptions

Parameter and fit index	Dual-change score	Proportional change score	Constant change score
Autoregressive coefficient (β)	-0.48^{*}	0.01^{*}	0.00^{a}
Constant change coefficient (α)	1.00^{a}	0.00^{a}	1.00^{a}
Intercept mean (μ_o)	1.91^{*}	1.90^{*}	1.91^{*}
Slope mean (μ_s)	0.93^{*}	0.00^{a}	0.01
Intercept variance (σ_o)	0.46^{*}	0.41^{*}	0.44^{*}
Slope variance (σ_s)	0.13^{*}	0.00^{a}	0.03^{*}
Correlation ($\rho_{o,s}$)	$.66^{*}$	$.00^{a}$	$-.22^{*}$
Error variance (Ψ)	0.32^{*}	0.37^{*}	0.32^{*}
Parameters	7	4	6
Degrees of freedom (*df*)	7	10	8
Chi square (χ^2)	45.96	189.72	70.67
CFI	.99	.95	.98
SRMR	.03	.05	.05
Compared with proportional change score	$\Delta\ \chi^2(3) = 143.76^{*}$		
Compared with constant change score	$\Delta\ \chi^2(1) = 24.71^{*}$		

Note. CFI = comparative fit index; SRMR = standardized root mean residual.
[a] Fixed parameter.
* $p < .05$.

We then estimated the bivariate LDS model. The model combines the dual-change univariate models with constrained autoregressive effects. We allowed the initial means and slopes to covary. In addition, we specified coupling paths from work safety perceptions to the LDS for job satisfaction and constrained them to be equal across time. These parameters were constrained to be equal across the time series. Similarly, we specified coupling paths from the job satisfaction variables to the LDS for work safety perceptions. The results of the bivariate LDS model are presented in Table 4. The model had acceptable fit, $\chi^2(11) = 48.63$, $p < .01$; CFI = .99; SRMR = .03. The intercepts were statistically significant for both job satisfaction and work safety perceptions, but the slopes were not. The autoregressive effects were not significant for job satisfaction or for work safety perceptions. This suggests that autoregressive and constant intraindividual change effects disappear when we consider the effects of the other variable at the previous time point.

Bivariate LDS Analyses

How Do the Intercepts and Slopes Relate to Each Other?

The intercept for job satisfaction had a negative correlation with the intercept for work safety perceptions ($r = -.40$, $p < .01$), suggesting that

Table 4. Parameters and Fit Indices for Bivariate Latent Difference Score (LDS) Model

Parameter and fit index	Bivariate	
	Job satisfaction	Work safety
Autoregressive coefficient (β_1)	−0.07	0.41
Autoregressive coefficient (β_2)	−0.05	0.41
Autoregressive coefficient (β_3)	−0.09	0.41
Constant change coefficient (α)	1.00[a]	1.00[a]
Coupling coefficient (γ)		
jsat to LDS_{safe1}	—	2.08*
jsat to LDS_{safe2}	—	2.04*
jsat to LDS_{safe3}	—	2.04*
safe to LDS_{jsat1}	0.34*	—
safe to LDS_{jsat2}	0.25	—
safe to LDS_{jsat3}	0.35*	—
Intercept mean (μ_o)	3.08*	1.92*
Slope mean (μ_s)	−0.34	−7.20
Intercept variance (σ_o)	0.13*	0.48*
Slope variance (σ_s)	0.06	0.41
Error variance (Ψ)	0.14*	.23*−.34*
Correlations		
Intercept jsat—intercept safe	−.40*	
Intercept jsat—slope jsat	.09	
Intercept jsat—slope safe	−.74*	
Intercept safe—slope jsat	−.73*	
Intercept safe—slope safe	−.15	
Slope safe—slope jsat	.03	
Parameters	33	
Degrees of freedom (*df*)	11	
Chi square (χ^2)	48.63	
CFI	.99	
SRMR	.03	

Note. jsat = job satisfaction; safe = work safety perceptions; CFI = comparative fit index; SRMR = standardized root mean residual.
[a] Fixed parameter.
* $p < .05$.

those higher in initial work safety perceptions tended to be lower in initial job satisfaction. The intercept for job satisfaction was not related to the slope for job satisfaction ($r = .09$, $p = .68$) but was significantly related to the slope for work safety perceptions ($r = -.74$, $p = .02$). The intercept for work safety perceptions did not correlate with the slope for work safety perceptions ($r = -.15$, $p < .73$) but did correlate with the slope for job satisfaction ($r = -.73$, $p = .01$). This suggests that initial levels of work safety perceptions were associated with less constant intraindividual change for job satisfaction, but was not related with constant intraindividual change for work safety perceptions. Finally, the two slopes were not related to each other ($r = .03$, $p = .97$).

Are There Spurious Autoregressive Effects?

In the univariate LDS models for job satisfaction and work safety perceptions, the autoregressive effects were statistically significant. However, it may be that these effects were spurious. For example, previous levels of work safety perceptions may cause intraindividual changes in job satisfaction. If the autoregressive effects for job satisfaction are not significant when controlling for work safety perceptions, then this may suggest that the autoregressive effects were observed because of shared variance between job satisfaction and work safety perceptions. This did appear to be the case in the example data. Both sets of autoregressive effects were no longer statistically significant when controlling for job satisfaction.

What Is the Direction of Influence?

Some of the more interesting aspects of bivariate LDS models are the coupling coefficients. These can indicate how levels of one variable influence subsequent intraindividual changes in the other variable or how intraindividual changes in one variable predict subsequent intraindividual changes in the other variable. As shown in Table 4, the coupling coefficients linking levels of job satisfaction to changes in work safety perceptions were statistically significant for all three LDSs ($\gamma = 2.08$, $p = .04$; $\gamma = 2.04$, $p = .04$; and $\gamma = 2.04$, $p = .04$, respectively). In addition, the coupling coefficients from work safety perceptions to changes in job satisfaction were significant for the first ($\gamma = 0.34$, $p = .02$) and third ($\gamma = 0.35$, $p = .02$) LDSs, but not the second ($\gamma = 0.25$, $p = .07$). This suggests a somewhat dynamic bidirectional relationship between the two variables. Intraindividual increases in work safety perceptions lead to intraindividual increases in job satisfaction at Times 2 and 4. Intraindividual increases in job satisfaction lead to greater intraindividual change in work safety perceptions for all three LDSs. It is also important to note that both the autoregressive effects and the constant intraindividual change slope means for both variables were no longer significant. This suggests that the LDS for both variables is primarily a function of the other variable's level at the previous time.

We also examined how intraindividual changes in job satisfaction and work safety perception relate to one another. To assess this, we specified a bivariate LDS model as before with the exception of specifying paths between the LDSs. For example, we specified the LDS job satisfaction at Time 2 to predict the LDS for work safety perceptions at Time 3 and also between Time 3 LDS for job satisfaction and Time 4 LDS for work safety perceptions. Similar paths were included from the LDSs for work safety perception to those for job satisfaction. We allowed the paths to freely vary to allow for the possibility that effect was not consistent across time. The resulting model fit reasonably well, $\chi^2(13) = 59.72$, $p < .01$; CFI = .99; SRMR = .04. Results suggest that the intraindividual changes in job satisfaction were not predicted by intraindividual changes in work safety perceptions at Time 3 ($\gamma = 0.08$, $p = .65$), but were at Time 4 ($\gamma = 0.57$, $p = .04$). Similarly, intraindividual changes in work safety perceptions at Time 3 were not predicted by intraindividual changes in job satisfaction at Time 2 ($\gamma = 0.09$, $p = .81$), but intraindividual changes in work safety perceptions at Time 4 were predicted by intraindividual changes in job satisfaction at Time 3 ($\gamma = 2.32$, $p = .04$).

The autoregressive effects and slope means were not significant for job satisfaction or work safety perceptions. Thus, the positive coefficient for intraindividual changes in job satisfaction predicting intraindividual changes in work safety perceptions at Time 4 suggested that increases in intraindividual changes in job satisfaction lead to intraindividual increases in change for work safety. The reverse also appeared to be true: The positive coefficient for intraindividual changes in work satisfaction predicting intraindividual changes in job satisfaction at Time 4 suggested that increased intraindividual changes in work safety perceptions lead to an increased intraindividual change in job satisfaction.

RECOMMENDATIONS FOR BUILDING AND FITTING LDS MODELS

Our major goal was to introduce LDS models as an alternative for occupational stress and health researchers interested in assessing intraindividual change. The LDS explicitly models latent intraindividual change scores, which can serve as predictors or outcomes of other variables. This allows researchers to test hypotheses involving intraindividual change. All of the techniques make similar assumptions about the data. For example, they all assume that the data are time structured; they need not be measured at equal intervals, but the unequal intervals need to be accounted for in the model. This is usually done by using different coefficients for the loadings on the slope factor.

We suggest testing a series of LDS models to determine whether the dual-change model is necessary. We also recommend testing alternative dual-change models. For example, the autoregressive effects or error variances can be freed across time. The efficacy of these models can be compared using chi-square differences tests. In addition to helping establish the best fitting model of intraindividual change, testing these alternative dual-change models can address some interesting research questions about the nature of how a variable changes.

Once suitable univariate LDS models are found, bivariate models can be estimated. These models can be somewhat susceptible to estimation problems when the models fail to converge. We have found that the more general models are easier to fit. We recommend beginning with a model specifying both sets of coupling parameters and allowing errors of the same time point to correlate. These coupling parameters and error correlations should be constrained to be equal across the time series. In addition, the covariances between intercepts and slopes are freely estimated. Alternative models can be specified by fixing or freeing these parameters.

It is likely that researchers will need to use a wide range of models to test their hypotheses. For example, a researcher may be interested in using more than four time points, the effects of an interaction term, and more complex nested models (time nested within employees, which are nested within organizations). As a general rule, after the latent change scores are defined, there is nothing the researcher cannot do that can be done with other change-modeling approaches. We also recommend that researchers consider power when using LDS models. Although LDS modeling has been used with a sample as small as 99, we strongly encourage researchers to obtain larger sample sizes to ensure appropriate power. Our experience has been that larger sample sizes ($N > 200$) encounter fewer estimation and modeling specification problems when using SEM software. Of course, the necessary sample size depends on the expected effect size and the parameters relevant to hypothesis testing. For a review of statistical power for dynamic SEMs, see Prindle and McArdle (2012).

Ultimately, the decision of which statistical approach to use depends on the theory of intraindividual change and the goals of the researcher. If autoregressive effects are suspected, then the LDS models may be best to use. If they are not, LGM is a viable option. Similarly, if constant change is not theorized, then cross-lag analyses might be more useful. Cross-lag analyses examine intraindividual change in relation to the previous standing on another variable without accounting for constant intraindividual change (slope).

Sometimes there may be no theory or expectations about whether or not autoregressive effects are present. In these situations, we recommend that researchers use the LDS model to test for autoregressive effects and constant intraindividual change by testing alternative models to determine the simplest best-fitting model of intraindividual change. We recommend starting with the dual-change model. This model provides information about both the autoregressive effects and constant intraindividual change. The fit of the dual-change model can be compared against proportional and constant change score models to determine whether both types of intraindividual change are necessary. Depending on the results of these comparisons, other types of intraindividual change analyses might be more useful. For example, if the proportional change score model is preferred, then cross-lag analyses might be more useful. If the constant change score model is preferred, then LGM and random coefficient modeling growth models might be more appropriate.

We see the main advantage of the LDS approach as that it explicitly models intraindividual change scores. Thus, these change scores can serve as predictors or outcomes. In addition, the autoregressive and constant intraindividual change parameters can be manipulated to model a number of dynamic intraindividual change patterns. A disadvantage of the LDS approach is that it can be somewhat difficult to specify correctly. The LDS approach assumes that the latent variables are equidistant in time. When the observed variables are measured at unequal intervals, this needs to be incorporated into the model. Another disadvantage of LDS modeling is that interpreting the result can be somewhat challenging because of its dynamic nature. Although being able to capture dynamic relationships can be seen as an advantage, they do not lend themselves to easy interpretation.

IMPLICATIONS FOR STRESS AND HEALTH THEORY

We believe LDS modeling may have important implications for developing and evaluating stress theories that emphasize intraindividual change. Researchers have recently begun to explore dynamic stress recovery models and explore the effects of intraindividual changes in nonwork recovery experiences over several days on work criteria (e.g., Binnewies, Sonnentag, & Mojza, 2010; Sonnentag & Natter, 2004). Although researchers in this field have made significant progress in understanding the stress recovery process by exploring intraindividual changes using journaling methods, LDS modeling can enable new questions to be asked.

A question of interest for researchers may be, whether recovery experiences on the weekend predict both constant intraindividual change in well-being over a workweek and when the greatest intraindividual change occurs during the workweek. In other words, weekend recovery experiences may predict a constant growth experience throughout the week while also leading to the greatest increase in well-being on the first day of the workweek. Indeed, researchers have found that recovery experiences generally have short-term effects (Sonnentag & Natter, 2004). However, it is unclear which form of recovery has the longest or most constant effects of well-being. These questions could be answered using an LDS change model of well-being with an external variable of weekend recovery experiences, which is similar to our example using age as an external variable. The slope would represent the constant growth experience and the LDS would represent the day-specific changes throughout a workweek.

Stress recovery researchers often refer to conservation of resources theory (Hobfoll, 1989, 2001) to describe the recovery phenomenon. According to conservation of resources theory, a person will strive to obtain new and protect resources. Resources include objects, conditions, personal characteristics, and energies. An experience of resource depletion is likely to be followed by an effort of resource allocation. However, Hobfoll describes these resources as relating in a web-like nature, which suggests that resource loss and gain will occur in spirals. In other words, prior levels of resources or well-being will influence subsequent experiences of resources or well-being. For example, an employee who experiences an increase in organizational support may be able to complete tasks more quickly and spend more time with family, which can increase family support. The increase in family support, in turn, enables the employee to handle family demands that may appear later on. The interconnected resources demonstrate that one positive resource gain may lead to additional resource gains, or positive spirals. The LDS approach will enable researchers to evaluate the effect of recovery experiences on affect spirals. According to conservation of resources theory, intraindividual change in affect may be dependent on previous intraindividual changes in affect. For example, a worker who experiences a demanding first day of the workweek may spiral out of control for the remainder of the workweek or until there is an opportunity to engage in appropriate recovery strategies.

Other psychological theories that describe the onset and duration of emotional experiences will greatly benefit from the LDS approach. Opponent process theory, for example, has been introduced to organizational researchers as a beneficial theory to describe the intraindividual changes in affect for an employee (Bowling, Beehr, Wagner, & Libkuman, 2005; Landy, 1978). Opponent process theory describes how emotional responses to stimuli are regulated through feedback loops. The feedback loops describe the short-term intraindividual changes to an employee's well-being. More specifically, an employee who experiences a reduction in demands will experience an initial positive emotional response (primary process), which will be followed by a inhibitory response (opponent process), which brings an employee's emotional state back closer to his/her constant state of equilibrium. The feedback loops and the short-term intraindividual changes may be best represented in the LDS models as the autoregressive coefficients and LDS change scores, respectively.

In addition to the feedback loops, people experience a state of hedonic equilibrium, which we believe is described by the slope in the LDS model. Equilibrium is a reference to a person's constant emotional pattern and does not necessarily indicate a lack of positive or negative affect. In other words, hedonic equilibrium is whatever steady change or state is unique to an employee. It is important to note that an employee's hedonic system is relatively stable because of the constant internal or external countervailing forces that constantly place pressure on the employee. LDS modeling would allow researchers to evaluate all components of the opponent process theory. For example, organizational researchers may be interested in understanding how fast affect emerges and how fast it fades. In addition, LDS modeling could be used to assess the strength of a person's opponent process and variables that are most likely to have the strongest effect on the opponent process. These questions are merely an introduction to the vast number of questions that can be empirically evaluated using LDS modeling. We encourage organizational stress theorists to consider LDS modeling when developing their study designs so that they can most appropriately test their theory driven hypotheses.

SUMMARY

We believe that LDS models provide occupational stress and health researchers flexibility to address a number of different research questions about intraindividual change compared with more traditional longitudinal models. LDS models allow for a more complete investigation of intraindividual change by incorporating both autoregressive and constant intraindividual change. Researchers can use univariate models to assess the correct model of intraindividual change and test hypotheses about autoregressive effects while allowing for constant intraindividual change. In addition, LDS models can serve as outcomes to help address questions about how other variables predict intraindividual change. Bivariate LDS models can be used to address questions about how intraindividual changes in one variable relate to another variable. This can provide some indication about whether or not the relationship is unidirectional and, if so, what direction the relationship is. Overall, LDS models will provide occupational stress and health researchers with a more accurate tool of modeling intraindividual change than has been used in previous research.

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