

9 Latent Growth Modeling Applied to Diary Data

The Trajectory of Vigor Across a Working Week as an Illustrative Example

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Emma and Harry both work in the service sector. They have normal jobs and spend five days a week, from Monday to Friday, at their workplace. It is Monday morning and they are about to start their working week. Emma has fully recovered from the weekend and, in light of the forthcoming interesting day at work, feels vigorous and lively. This is also true for Harry, but during the course of the week, he becomes increasingly less vigorous and he reaches a low in terms of energy on Wednesday. Thursday morning, however, is a turning point for Harry. In sight of the weekend, he starts to feel more vigorous again. His cheerfulness and spirits rise as he eagerly awaits the hockey game on Saturday night. His vigorous feelings steadily increase and reach a peak on Sunday. While Harry evinces a drop in vigor across his working week, Emma does not. In contrast, her energetic mood increases slightly as the week proceeds. The inspiring and supportive team at work makes her feel increasingly more energetic as the days pass. Furthermore, she looks forward to hiking with her friends on the upcoming weekend.

The example of Emma and Harry depicts two possible patterns of change with regard to vigor across a working week. This example suggests that for both Emma and Harry, intra-individual variability in vigor is time-structured, but that they also differ in their progress across the week: Harry's vigor has a U-shaped pattern, whereas Emma's follows a linear pattern. One might ask whether a typical pattern of change with regard to vigor exists. Supervisors, for instance, could use this knowledge to determine how the workload should be structured in order to maintain stable levels of performance. Alternatively, this information could be used to gauge when would be best to express esteem for employee motivation. Furthermore, one might ask why Emma and Harry differ in their patterns. What are the personal and situational factors explaining different patterns of change across the week? Knowledge about differences in employees' vigor trajectories could also be beneficial for daily "micro-interventions." Conceptually, such questions refer to the issue of time-structured intra-individual variability (Ram & Gerstorf, 2009) and of inter-individual differences in these intra-individual processes.

These questions can be tackled using latent growth models¹ (LGMs; Bollen & Curran, 2006; Singer & Willet, 2003). LGMs provide a potentially powerful approach to longitudinal data requiring analysis of changes, including both decreases and increases, in a latent construct across time. The basic idea of LGMs is that a set of repeated measures is systematically related to time. For instance, a positive linear growth in vigor would mean that vigor increases systematically from day to day for an average individual. In contrast to traditional methods such as ANOVA or ordinary least square (OLS) regressions, LGMs estimate growth curves that are allowed to vary across individuals. Thus, variance in the estimated growth curves is regarded as meaningful variance (i.e. differences in growth between individuals) rather than error variance. Hence, LGMs simultaneously take into account the form (e.g. linear, curvilinear) and rate of the change, as well as inter-individual differences in the rate of change. LGMing has a number of additional advantages, such as its increased statistical power, compared to traditional methods (see McArdle, 2009).

The idea of growth is incorporated into various theoretical frameworks in industrial and organizational (I/O) psychology. For instance, health problems are thought to develop as a result of stressors at work (Semmer *et al.*, 2005). Motivation is thought to grow because of appropriate resources at work (Schaufeli & Bakker, 2010). Intellectual flexibility is thought to increase with fewer job restrictions (Schooler *et al.*, 1999), while conflicts are thought to escalate due to inappropriate conflict management (De Dreu, 2005). This suggests a clear need to study time-structured change (e.g. development) in the field of industrial/organizational psychology (I/O) psychology. Despite this need, it has rarely been investigated how relevant variables develop over time and what the important factors are that initiate or alter development.

A review of the literature regarding I/O psychology reveals that very few studies have applied LGMs. We are aware of 27 such studies that have been published in peer-reviewed journals. The earliest study is by Ployhart and Hakel (1998), who investigated time-structured intra-individual variability in job performance. Later studies using LGMs touch upon a broad range of topics, including the development of attitudes and health-related variables in particular phases of an individual's working life (e.g. organizational entry; Jokisaari & Nurmi, 2009). Other studies report the effect of work stressors on the development of well-being or attitudes (Garst *et al.*, 2000; Grech *et al.*, 2009), or the effects of job resources on the development of job-related flow (Mäkikangas *et al.*, 2010).

The rather low number of studies using an LGM approach may be partly explained by the fact that the majority of studies are still cross-sectional in nature and therefore do not allow intra-individual processes to be taken into account. However, this argument does not accommodate the recently observed increase in diary studies being published (Ohly *et al.*, 2010). Diary studies are short-term longitudinal studies through which short-term growth processes can be investigated. In spite of this, LGMs are rarely applied to diary data. Most studies with a focus on growth span months or years. Therefore, they cover long-term developmental processes. However, there is evidence of relevant short-term variability that is

time-structured (e.g. fatigue within and across consecutive working days; Grech *et al.*, 2009). Another reason for the low number of studies that have applied LGMs may be that researchers are not yet familiar with this rather new methodology and may not always realize that their research question could be tackled elegantly through the application of LGMs.

Taken together, LGMs are regarded as a powerful analytical framework for studying change processes. The few studies that have applied LGMs have focused on long-term developmental processes. Given this state of affairs, and the increasing interest in and availability of data to study short-term intra-individual processes, the goal of this chapter is to give a step-by-step example of the application of LGMs to diary data. Specifically, we will use the pattern of vigor across a working week as an illustrative example in order to give a non-technical introduction to LGMs within a structural equation modeling (SEM) framework. For this reason, we will briefly introduce vigor as a state concept, present our data and summarize some basic conceptual issues regarding change in relation to our example. We will continue by discussing a central prerequisite to conducting latent growth modeling (i.e. longitudinal measurement invariance) and how to test for it. We then will compute a basic LGM that captures time-dependent change in vigor across a working week. Finally, we will show, as an example, how to analyze inter-individual differences in a LGM. In this chapter, we aim to inspire other researchers to study the broad field of growth-related research questions in general and short-term growth in particular.

State Vigor

The construct of vigor has recently received a great deal of attention from various scholars, who have described it as a central facet of work engagement (Bakker *et al.*, 2008), as a multi-dimensional construct (Shraga & Shirom, 2009), or as a mood facet (Cranford *et al.*, 2006). Upon reviewing the literature, it becomes apparent that efforts have been made to relate vigor to other important constructs in the workplace. Meta-analytic results, for instance, show that vigor is related to resources at work (e.g. feedback), to a lesser extent to demands (e.g. work–family conflict), and to important outcomes such as performance (Halbesleben, 2010).

Most studies conceptualize vigor as a rather stable construct; however, vigor can also be regarded as a state concept (Cranford *et al.*, 2006). In this sense, feeling vigorous refers to a state of positive energy that, according to an interview study, lasts a few minutes to a maximum of a few days (Shraga & Shirom, 2009). The question is whether these changes in vigor are systematically related to time. More specifically, does vigor follow a certain pattern of change across a working week? Descriptive results from a recent study by Cranford *et al.* (2006) support the idea of systematic weekly changes in levels of vigor. An inspection of the average vigor trajectory of 164 graduate students (Figure 2 in Cranford *et al.*, 2006) suggests that vigor embodies a U-shaped pattern over the course of a week, in a similar way to the example of Harry. In the remainder of this chapter, we will examine

whether or not such a pattern is apparent in our example data drawn from the working population.

The Example Data

For illustrative purposes, we will use data from a diary study of 116 employees (64 percent females) working in various organizations. Mean age of the participants was 34.0 ($SD = 12.7$). Before the diary study started, the participants completed a general questionnaire, including trait measures, general measures of their work situation (e.g. job resources), and demographic variables. After this, the participants were asked to fill in diaries before work, after work, and before sleeping, for two weeks, including weekends. Thus, most participants filled in three diary entries per day for 14 days. For reasons of simplicity, we will focus only on the morning diary entries from one week (seven days). In the morning diary, we included a scale to measure state vigor. This scale was developed by Cranford *et al.* (2006). It consists of three items and is based on the Profile of Mood States (McNair *et al.*, 1992). Every morning, the participants had to indicate the extent to which they felt vigorous, cheerful, and lively (1 = *not at all*; to 5 = *extremely*) at that moment in time.

Change Versus Variability

LGMs are a means by which to analyze change within individuals. Change in vigor can be analyzed using different time scales that correspond to the different conceptualizations of change in the literature. For instance, one could be interested in how trait vigor changes across the lifespan (for an analogous research question regarding self-esteem, see Orth *et al.*, 2010). However, a complementary perspective to this long-term approach (i.e. development) is the investigation of short-term, relatively rapid, and more or less reversible change processes (i.e. daily variability in energetic resources). Most diary studies focus on this kind of change. Highlighting the differentiation between these two types of change, Nesselroade (1991, p. 215) has termed the former *intra-individual change*, which is defined as “more or less enduring changes that are construed as developmental.” The latter type is termed *intra-individual variability*, which refers to “relatively short-term changes that are construed as more or less reversible and that occur more rapidly than the former.”

Moreover, Ram and Gerstorf (2009) suggest that intra-individual variability can be further differentiated. They highlight that there is intra-individual variability that is unstructured in relation to time. For instance, the occurrence of success at work is not usually ordered in time (i.e. it is equally likely to occur in the morning or in the afternoon, and on Monday or Friday). Ram and Gerstorf (2009, p. 779) use the term *net intra-individual variability* to refer to “short-term within-person changes that are analyzed as being unstructured in relation to time.” In contrast, *time-structured intra-individual variability* is defined as “changes that are systematically ordered in time.” The circadian rhythm is an example of the second

kind of variability. This latter distinction is important for the purpose of this chapter. In asking whether or not there is a typical pattern of change in vigor over a working week, we are implicitly asking whether vigor follows a time-dependent pattern of change or whether variability in vigor is randomly fluctuating with regard to time. Analytically, we will answer this question by comparing different models that assume vigor to be either: (a) a construct that varies within person, while variance is treated as unrelated to time (i.e. the state model); (b) a construct consisting of a stable part (i.e. trait) and a variable part that is unrelated to time (i.e. the state-trait model); or (c) a construct with intra-individual variance that is related to time (i.e. LGMs). Before we do this, we need to discuss measurement invariance, which is an important prerequisite to modeling longitudinal data.

Importance of Measurement Invariance When Investigating Longitudinal Data

In longitudinal research, it is crucial to ensure that the same construct is measured at each point in time (i.e. measurement invariance or factorial invariance). For an unambiguous interpretation of change in a construct, this change needs to happen at the level of the construct (i.e. latent variable) and not at the level of the observed variables that measure the construct (Ferrer *et al.*, 2008). Possible threats to measurement invariance are changes regarding the interpretation of item content or a change in the level of items that cannot be explained by a change in the latent construct. For instance, the extensive repetition of measurements within a short time interval might be a cause for concern in diary studies. In response to previous assessments, participants subjectively redefine the constructs of interest so that they are no longer comparable between states.

In addition to invariance in terms of configuration (i.e. the same indicators and latent constructs must be specified at each point of measurement), three levels of factorial invariance can be distinguished (e.g. Widaman & Reise, 1997). Weak factorial invariance occurs when the factor loadings of each indicator are invariant over time. Strong factorial invariance requires, in addition to equal factor loadings, the intercept of each indicator to be invariant over time (i.e. the relative contribution of each intercept to the scale mean should be the same over time). Finally, strict factorial invariance also requires the unique variance (i.e. error variance) of each indicator to be equal over time. In practice, strict factorial invariance is unlikely to occur, and violations of this assumption can be tolerated (e.g. Sayer & Cumsille, 2001). Hence, before modeling change at the latent level, it is necessary to test for and to establish the presence of (at least) strong factorial invariance.

The Basic LGM

The general principle of an LGM is that a given set of repeatedly measured constructs is functionally related to time. The model depicted in Figure 9.1 represents a basic second-order LGM (Ferrer *et al.*, 2008; Sayer & Cumsille, 2001; for an introduction to first-order LGMs, see: Bollen & Curran, 2006). This second-

order LGM consists of: (a) a measurement part (confirmatory factor analyses [CFA] for longitudinal data), where multiple observed variables (i.e. items; in this case, three items: X; Y; W) are used as indicators of a latent construct (i.e. first-order factor; f) at each measurement point; and (b) a structural part, where the growth in the latent construct over time is modeled through a second-order intercept factor (f_0) and a slope factor (f_s). Thus, the growth parameters capture time-dependent variation among the latent true scores. More specifically, the intercept represents a constant value of the construct for any given individual across time. This is apparent from the factor loadings of the intercept factor, which are fixed to 1. The latent slope factor captures the rate of change across time for any given individual. In order to estimate the intercept and slope of the growth curve, not only must the covariance structure of the data be taken into account (as in ordinary cross-lagged models, for instance), but the mean structure must be as well. This is because, in LGMs, both the relationships between variables and changes in the intercepts of the variables are of interest. The factor loadings ($\beta_1 - \beta_0$) determine the shape of the curve. For instance, if we assume that the measurement points are equally spaced (such as daily measures), and that there is consecutive linear growth from the first day onwards, the factor loadings would then have numerical values of $\beta_0 = 0$ for the first day, $\beta_1 = 1$ for the second day, $\beta_2 = 2$ for the third day, and so forth. Later in the chapter, we will discuss how non-linear (e.g. quadric) growth can be modeled. In general, thorough theoretical and empirical consideration is required concerning questions of how to incorporate time into LGMs and how to decide upon the level of complexity of the change trajectory. For an in-depth treatment of issues relating

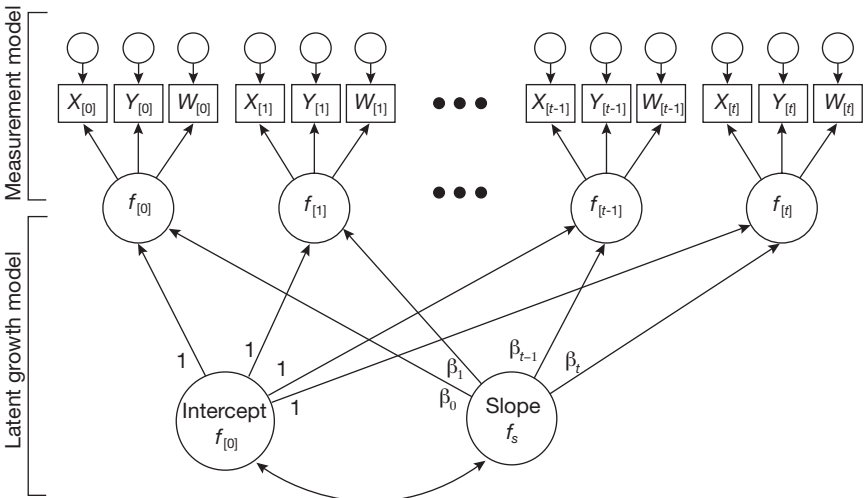


Figure 9.1 Simplified path diagram of a second-order linear LGM

Note

Latent variables are represented by circles and manifest variables by squares. Not depicted in this figure are the intercepts of the manifest and latent variables, the covariances among the same manifest variables at adjacent measurement points, and the variances of the latent variables.

to time and the complexity of LGMs, we recommend that the interested reader consult Bollen and Curran (2006), Blozis and Cho (2008), or Ram and Grimm (2007).

In order to illustrate the basic LGM shown in Figure 9.1, we will apply it to our data. We measured vigor with three items (vigorous, cheerful, and lively), which represent the manifest indicators X, Y, W in Figure 9.1. By means of CFA, these items were used to “build” a latent construct of vigor at each of the seven measurement points. The growth (i.e. time-structured intra-individual variability) of these latent true scores was then modeled through a second-order latent intercept and latent slope. For reasons of simplicity, let us assume at this stage that we specified a linear growth process as described above. The mean of the latent intercept represents the average vigor score of the sample on Monday, while the variance of the latent intercept captures the amount of inter-individual difference in vigor on Monday. The mean of the latent slope represents the average rate of change in vigor per day of the sample. A positive mean implies an increase and a negative mean a decrease over time. Finally, the variance of the latent slope represents inter-individual differences in the rate of change.

The Basic Analytical Steps When Building an LGM

Analytically, building an LGM is a three-stage procedure. First, measurement invariance is tested by fitting a CFA for longitudinal data. Second, individual growth trajectories are fitted to the latent construct, which is measured on multiple occasions. Note that, at this point, we model the within-individual aspects of the LGM, resulting in a sample-mean growth trajectory including variance components that capture inter-individual differences in the growth curve. It is imperative at this stage to correctly specify a growth trajectory that is theoretically meaningful and empirically accurate. Third, variables are introduced that are expected to predict inter-individual differences in growth.

Now, we will follow these steps and build an LGM with our sample data. First, we test measurement invariance, and then we compare the different models in order to decide: (a) whether an LGM for vigor scores over a week is empirically meaningful; and (b) how the shape of the curve should best be specified. In the final step, we introduce possible predictor variables (i.e. the amount of positive feedback received at work, trait vigor) for the specified LGM. Analyses were conducted using Mplus (Version 6; Muthén & Muthén, 1998–2010). Annotated Mplus syntax of all the models specified in this chapter can be downloaded from <http://science.cloud-solutions.net>.

First Step: Testing Measurement Invariance

In order to test for measurement invariance, we follow the procedure recommended by Ferrer *et al.* (2008). We start with an unrestricted longitudinal CFA model (CFA1). In this model, the first item is used as a reference indicator at each point

of measurement. Accordingly, its factor loading is fixed to 1. Furthermore, all seven factors (i.e. the latent scores for vigor from Monday to Sunday) are allowed to correlate with each other, and the uniqueness of individual indicators (i.e. measurement error) is modeled as being correlated over time in order to account for consistency in item-specific variance. In the next model, we fix the factor loadings of each indicator to be equal across time (CFA2) and compare this model with the CFA1 model. Next, we also fix the intercepts of each indicator to be equal over time (CFA3) and compare this model with the CFA2 model. If the more constrained model does not yield a worse fit than the less constrained model, then the constraints are empirically justified. This can be tested by using the X^2 -difference test and by comparing the sample-size adjusted Bayesian information criterion (ABIC). More specifically, if the more restricted model does not show a significant increase in X^2 , the restriction is justified. Moreover, the ABIC should be lower in the restricted model. To evaluate the overall goodness of fit, we also use the indices suggested by Ferrer *et al.* (2008), namely the X^2 statistic, the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the Tucker–Lewis index (TLI).

Table 9.1 summarizes the results of these tests with our sample data. In general, all three measurement models show good fit indices (see Hu & Bentler, 1999). In terms of measurement invariance, neither the restriction of invariant factor loadings ($\Delta X^2(12) = 5.7, p = 0.93$) nor the restriction of invariant indicator intercepts ($\Delta X^2(12) = 17.4, p = 0.14$) led to a relevant loss of information. Moreover the ABIC decreases as the model becomes more restricted. Thus, there is evidence for strong factorial invariance in our measure of vigor. At this point, we can be confident that potential changes across time are “true” changes in the construct and not changes at the level of the observed variables. This is crucial for the interpretation of an LGM (see Ferrer *et al.*, 2008). The final measurement model (CFA3) can be regarded as a latent state model with invariant factor loadings and intercepts for each indicator. For the remainder of the chapter, we will refer to this as the state model.

Table 9.1 Fit indices of the measurement models tested

Model	X^2	df	RMSEA	90%-CI	TLI	CFI	ABIC
Tests of measurement invariance							
Unconstrained model (CFA1)	120.5	105	0.036	0.000–0.062	.99	.99	4764
Invariant factor loadings (CFA2)	126.2	117	0.026	0.000–0.055	.99	.99	4751
Difference of 2 and 1	5.7	12					
Invariant intercepts (CFA3)	143.6	129	0.031	0.000–0.057	.99	.99	4749
Difference of 3 and 2	17.4	12					

Notes

RMSEA = root mean square error of approximation; 90%-CI = confidence interval for RMSEA; TLI = Tucker–Lewis index; CFI = comparative fit index; ABIC = Bayesian information criterion, adjusted for sample size.

Second Step: Specification of the Form of Change

In this section, we will answer two consecutive questions. First, is the daily intra-individual variability in vigor time-structured over the week (i.e. is it possible to fit an LGM model to our vigor data)? Second, what is the form of this time-structured variability (i.e. what does the average vigor trajectory over the course of a week look like)? Again, we will achieve this by comparing alternative models with each other. The ultimate goal of comparisons such as these is to find a model that is theoretically meaningful and parsimonious without losing important information which is “hidden” in the data. Thus, empirically speaking, the final model should show an acceptable goodness of fit and should be as parsimonious as possible. We evaluate the overall goodness of fit using the X^2 statistic, the RMSEA, the CFI, and the TLI. In order to compare alternative models, we use, in addition to the ABIC, the Akaike information criterion (AIC). This gives us a broader basis for decision-making than the ABIC alone. Both indices provide information on the fit of a model while also considering the parsimony of the model (i.e. including a penalty function as the amount of parameters to estimate increases). Thus, when comparing two models, the smaller the information criteria, the better the fit.

In practice, it is common to directly specify different LGMs (e.g. linear LGM, curvilinear LGM) and compare these models with each other, in order to determine the shape of the trajectory. For illustrative purposes, however, we will also consider a state-trait model of vigor that acts as an intermediate step between the state model and the LGMs. All in all, this is a somewhat more rigorous test to determine whether a growth-based approach is more appropriate than simply comparing different LGMs to one another.

It is worth noting that vigor may not only have a state component, but also a trait component. Thus, variance in state vigor may not be exclusively intrapersonal but also interpersonal. Different individuals may fluctuate at different levels. Indeed, calculations with our sample data show that 43 percent of the total variance in vigor is intrapersonal, whereas 57 percent is interpersonal². Conceptually, this could indicate a latent state-trait model (STM), where the covariances among the first-order factors are structured through a second-order trait factor (see Figure 4 in the supplemental material at <http://science.cloud-solutions.net>). The variance in the first-order factors that cannot be explained by the trait factor can be interpreted as “pure” state variance. Specifying a basic STM, like a basic state model, is based on the assumption that variance is not time-dependent. The trait factor, by definition, captures only interpersonal variance and hence cannot be related to time. As for the state part of the model, time has not been incorporated as a structuring element.

This constitutes an important difference between an STM and a LGM. By including a slope factor in the LGM, we proceed on the assumption that intra-individual changes in vigor over the course of a week have a certain pattern that is related to time. Moreover, in the case of daily diary data and a construct that includes state and trait components such as vigor, one can assume that the intercept of the growth model captures mostly the trait component. One frequently specified

trajectory with regard to LGMs is a linear trajectory. In addition, with regard to vigor, it seems plausible that there is a linear pattern across the week. To clarify, assuming a linear growth does not mean that the average trajectory of the sample has to increase or decrease across the week. It might be that, on average, the linear slope is zero, which would imply that aggregating all of the individual linear slopes would result in no change across the week. However, the slope may feature a significant amount of variance between individuals, meaning that some individuals show an increase while others show a decrease, resulting in a zero slope at the aggregated level. As a linear LGM is often a starting point from which to specify the form of a growth process, we will specify a linear LGM as a third model.

As mentioned above, the study by Cranford *et al.* (2006) suggests that vigor has a curvilinear pattern over the course of a week. Specifically, it seems that, on average, vigor decreases from Monday to mid-week and then increases again until Sunday (U-shape). This suggests that a quadratic slope factor should be included in the model. Figure 9.2 illustrates this specification. The growth process is now defined by three factors: an intercept, a linear slope, and a quadratic slope. The factor loadings for the quadratic slope are set as the squares of the linear terms. For each of the factors, the mean, the variance, and the three covariances between them are estimated. Thus, a quadratic LGM is the fourth model that we will test against the others.

The application of these four models to our sample data shows that the STM and the linear LGM yield a poorer fit to the data compared to the state model (Table

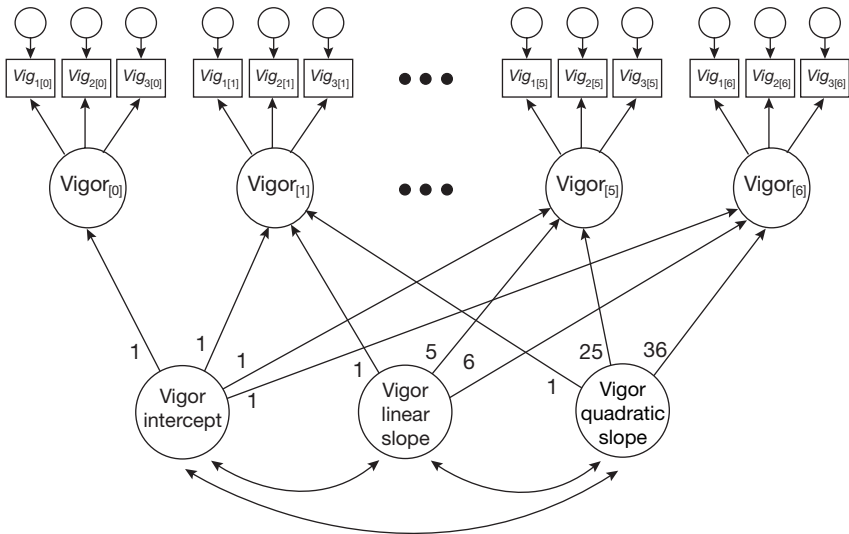


Figure 9.2 Simplified path diagram of the second-order quadratic LGM for vigor

Note

Latent variables are represented by circles and manifest variables by squares. Not depicted in this figure are the intercepts of the manifest and latent variables, the covariances among the same manifest variables at adjacent measurement points, and the variances of the latent variables.

9.2). Even though the values of RMSEA, TLI, and CFI suggest a good overall fit of these two models, the X^2 values do not. Moreover, compared to the state model, the STM shows an increase of the AIC and ABIC, while the linear LGM exhibits an increase of the ABIC. This suggests that the higher parsimony of the STM and the linear LGM, in comparison to the state model, is too “costly” in terms of decreased fit. In contrast, the quadratic LGM shows a good overall fit (X^2 , RMSEA, CFI, TLI) and the lowest AIC and ABIC values compared to the other models. This suggests that the quadratic LGM fits the data best. According to these results, we can answer the questions raised at the beginning of this section, by stating that vigor does have a time-structured pattern across the week. This pattern is best described using a linear and a quadratic growth factor.

Table 9.3 summarizes the parameter estimates for this quadratic LGM (see LGM without time-invariant covariates [TICs]; we will explain the LGM with TICs below). The mean of the intercept (μ_{f_0} ; estimated average vigor value on Monday) is significantly different from zero and varies significantly between individuals ($\sigma^2_{f_0}$; estimated variance of the vigor score on Monday). Furthermore, on average, vigor neither increases nor decreases over the course of the week. The mean of the linear slope (μ_{f_l}) and the mean of the quadratic slope (μ_{f_q}) are not statistically different from zero. More important, however, is the significant inter-individual variability in the slopes ($\sigma^2_{f_l}$, $\sigma^2_{f_q}$) of the model. This suggests that some individuals show increases or decreases in vigor across the week and that these changes are curvilinear. For the multivariate study of LGM, the latter result is crucial. Even if the mean intra-individual change is low, the variability in intra-individual change should be significant, in order to justify an investigation of potential predictors of growth factors.

Third Step: Adding Covariates to the LGM

Once the shape of the growth curve is correctly specified, covariates (i.e. predictors) can be incorporated into the LGM. The inclusion of covariates into the model results in a conditional LGM because the fixed and random parts of the model are then

Table 9.2 Fit indices of the specified structural models

<i>Model</i>	X^2	df	<i>RMSEA</i>	<i>90%-CI</i>	<i>TLI</i>	<i>CFI</i>	<i>AIC</i>	<i>ABIC</i>
State model	143.6	129	0.031	0.000–0.057	.99	.99	4800	4749
State-trait model	172.3*	143	0.042	0.004–0.064	.98	.98	4801	4756
Linear growth model	183.5*	152	0.042	0.009–0.063	.98	.99	4794	4753
Quadratic growth model	163.1	148	0.030	0.000–0.054	.99	.99	4782	4739

Notes

RMSEA = root mean square error of approximation; 90%-CI = confidence interval for RMSEA; TLI = Tucker–Lewis index; CFI = comparative fit index; AIC = Akaike information criterion; ABIC = Bayesian information criterion, adjusted for sample size.

* $p < .05$, ** $p < .01$.

Table 9.3 Parameter estimates for the quadratic LGMs of vigor with and without TICs

Model	<i>LGM without TICs</i>		<i>LGM with TICs</i>	
	Coef.	SE	Coef.	SE
Fixed effects				
Mean of intercept (μ_{j0})	2.882**	0.090	2.879**	0.091
Mean of linear slope (μ_{j1})	-0.035	0.046	-0.037	0.044
Mean of quadratic slope (μ_{jq})	0.012 [†]	0.008	0.013 [†]	0.007
Random effects				
Variance of intercept (σ^2_{j0})	0.527**	0.113	0.359**	0.092
Variance of linear slope (σ^2_{j1})	0.104**	0.037	0.084*	0.035
Variance of quadratic slope (σ^2_{jq})	0.003**	0.001	0.003**	0.001
TICs				
Effects on intercept				
Trait vigor			0.75**	0.16
Positive feedback			-0.09	0.06
Effects on linear slope				
Trait vigor			-0.09	0.09
Positive feedback			0.10**	0.03
Effects on quadratic slope				
Trait vigor			0.02	0.02
Positive feedback			-0.01*	0.01

Notes

All values are maximum likelihood estimates from Mplus. *Coef.* = unstandardized coefficient; *SE* = standard error. Further information about the two models (Mplus syntax and figures) can be found at <http://science.cloud-solutions.net>.

[†] $p < .10$, * $p < .05$, ** $p < .01$.

dependent on the covariates. Basically, there are two different types of predictor. One type is TICs. These are (relatively) stable predictors that do not vary over time, such as demographic variables (i.e. gender), trait variables (i.e. trait vigor) or stable work conditions (i.e. general job resources). Typically, these variables are used to explain inter-individual variance in the LGM. Thus, they are incorporated as predictors of the intercept and the slope factors. For instance, one might investigate whether a certain TIC is associated with a higher initial value (intercept) or with a steeper increase over time (slope). The other type of covariate is referred to as time-variant covariates (TVC). These are variables that vary across time and are repeatedly assessed (i.e. sleep quality the night before or goal attainment the previous day). TVCs are incorporated into the LGM in a different way: they directly predict the latent true scores (f_s in Figure 9.1), while controlling for the influence of the growth factors. As a result, the repeated latent true scores are simultaneously predicted by the specified growth factors and the TVCs at that point in time. Due to limitations in the scope of this chapter, we will only illustrate how TICs can be included in LGMs. Readers who are interested in TVCs are referred to Bollen and Curran (2006) for the treatment of this topic within an SEM framework and to Singer and Willet (2003) for the applications in a multilevel framework.

In order to illustrate the inclusion of TICs, we will use trait vigor and the amount of positive feedback generally received at work. We chose these variables because they should predict different parts of our quadratic LGM. Stable inter-individual differences in vigor (i.e. trait vigor) should mainly be related to the level of the weekly vigor trajectory (i.e. intercept factor). The amount of positive feedback received at work is also more likely to influence the rate of change (i.e. slope factors). Positive feedback is an important job resource (Grebner *et al.*, 2010) that is associated with vigor (Halbesleben, 2010). Frequent positive feedback throughout the week should energize and motivate employees (Kluger & DeNisi, 1996), and should consequently prevent a drop in vigor over time. This reasoning leads to the assumption that the general amount of positive feedback an employee receives from his/her supervisor may positively influence the level of vigor as well as the pattern of change with regard to vigor over the week.

In order to investigate whether trait vigor and the general amount of positive feedback received at work can explain inter-individual differences in time-dependent changes in vigor, we include these two variables as TICs in the quadratic LGM. Trait vigor and the general amount of positive feedback were assessed using the general questionnaire that was completed before the diary study began. Trait vigor was measured with the same three items which were used to measure state vigor, but the instructions asked the participants to indicate the extent to which they had felt vigorous, cheerful, and lively in the past 30 days. The general amount of positive feedback from the supervisor was assessed with a single item. The participants had to indicate how often they received positive feedback from their supervisor (1 = *never* to 5 = *constantly*). Hence, in the quadratic LGM, we use a CFA to build a latent true score of trait vigor, which is modeled to predict the intercept, the linear slope, and the quadratic slope of vigor. The amount of positive feedback is introduced as a manifest variable that also predicts the intercept, linear, and quadratic slope.

Table 9.3 summarizes the results of this model (LGM with TICs). Trait vigor is positively associated with the intercept, but not with the slope factors of the LGM. Thus, trait vigor seems to influence the general level of weekly vigor, but not the linear or quadratic rates of change. In contrast, the general amount of positive feedback received at work only explains variance in the slope factors but not in the intercept factor. The effect of a TIC on a slope factor can be regarded as a two-way interaction between time and the TIC. Thus, positive feedback moderates the association between time and vigor. Analogously to the interpretation of interactions in an OLS regression, plotting vigor trajectories for different conditional values of positive feedback is one way to interpret the pattern of the interaction (Preacher *et al.*, 2006). Following the advice of Aiken and West (1991), we chose values that are one standard deviation below and above the sample mean. Figure 9.3 depicts vigor trajectories for participants who received infrequent ($-1 SD$) and frequent ($+1 SD$) positive feedback from their supervisors. Individuals who generally receive frequent positive feedback have an almost linear trajectory that increases as the week advances. In contrast, employees who receive little positive feedback followed a U-shaped pattern, with a low in the middle of the week. These results suggest

that the general amount of positive feedback received from one's supervisor influences the pattern of change with regard to vigor over a working week. In other words, frequent positive feedback can prevent energetic lows or even increase vigor from day to day. More generally, these results confirm the importance of appreciation at work (see Semmer *et al.*, 2007).

It should be noted that the main purpose of this analysis was to illustrate the ways in which an LGM can be applied to diary data and how TICs can be incorporated into a previously specified LGM. For reasons of clarity and comprehensibility, we focused on a time-frame of one week and therefore simplified our analysis accordingly. As the pattern of change in vigor from one week to the next is likely to be a cyclic phenomenon, more than one week should be taken into account. For instance, our results could be cross-validated with data from the second week, or an LGM for two weeks could be modeled with cyclic functions (see Beal & Ghandour, 2011). Nevertheless, our simplified example allowed us to show the potential of LGMs in diary research and to provide a step-by-step application for a possible research question. In the remainder of the chapter, we will highlight possible extensions of our example.

Further Applications of LGMs in the Analysis of Diary Data

We showed that vigor follows a time-dependent pattern of change across a working week. However, we also noted that Emma and Harry follow different patterns. Thus, one may be interested not only in the typical pattern of time-dependent changes in vigor, but also in the question of whether different types (classes) of patterns exist. An extension of LGM called growth mixture modeling (GMM) addresses such research questions and helps to identify unobserved subpopulations

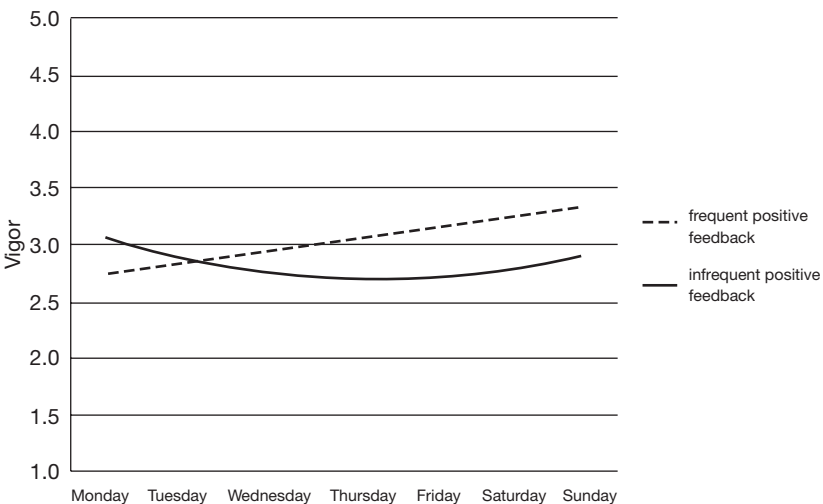


Figure 9.3 Trajectory of vigor as a function of positive feedback at work

(classes) with similar patterns of change. For example, Mäkikangas *et al.* (2010) investigated classes of change in job resources and how these are related to flow. GMM is, therefore, an interesting way to examine whether different classes of change exist, how frequent such classes are, and how these classes are related to other variables, such as work or personal characteristics. A non-technical introduction to GMM is presented by Wang and Bodner (2007).

In our empirical example, we conceptualized state vigor as an outcome of other variables (trait vigor and feedback). Slope variables, however, may also be used as predictors. For example, the pattern of change in vigor from Monday to Friday may predict the need for recovery and recovery-related activities during the weekend. Moreover, patterns of change can simultaneously be used as an outcome and a predictor, providing opportunities to test mediation models (e.g. work characteristics shape the trajectory of vigor during the working week, which has an impact on recovery activities at the weekend).

In the present chapter, we restricted our focus to a univariate trajectory. However, combining two or more trajectories is possible and may shed light on the parallel changes in two or more variables. For example, does a change in job resources go hand-in-hand with a change in vigor, and vice versa (Bakker, 2010)? Bivariate LGMs can provide information about parallel intra-individual changes over time, but they do not provide a basis for drawing conclusions regarding whether or not one of the variables predicts subsequent changes in the other variable because the parameters of the curves are based on an identical time interval. In order to investigate a temporal sequence of two or more variables, bivariate latent difference score (LDS) analyses are more appropriate (see McArdle, 2009; for an application, see Orth *et al.*, 2008).

Finally, we limited our discussion to individual patterns of change and neglected the fact that employees often work in teams and live with a partner. Considering the social context, however, may be conducive to forming an understanding of patterns of change in outcomes such as vigor. For example, previous research has shown that people's moods are linked to the mood of their teammates (emotional contagion; Totterdell *et al.*, 1998) and that work engagement may be transferred to one's partner at home (crossover; Bakker *et al.*, 2005). Simultaneously analyzing the patterns of change of dependent individuals would provide a more elaborate understanding of change, but would also require more sophisticated procedures because such data are nested. Innovative methods such as multilevel SEM, however, are capable of handling these kinds of data structures (for an introduction, see Heck & Thomas, 2009).

Conclusion

In this chapter, we discussed issues relating to the application of LGMs to diary data. Our goal was to demonstrate the potential and the possibilities this method provides. We pointed to important conceptual distinctions between different kinds of intra-individual change, providing a framework for the application of LGMs.

We discussed measurement invariance as a crucial prerequisite when modeling longitudinal data, including diary data. We built a quadratic LGM with TICs in a step-by-step process and illustrated this process with sample data. Overall, we hope that our introduction to this promising method will inspire many I/O researchers to apply it to a variety of research topics and that it will ultimately lead to happy days in the lives of many researchers.

Notes

- 1 In the literature, different terms are used to refer to this method. Alternative terms include latent curve analysis and latent trajectory modeling, among others. In this paper, we have adopted the term “latent growth model” because it is probably the most commonly used term. Researchers who prefer names which do not include the word “growth” explain this by referring to the fact that this framework can also be applied to cases where, on average (i.e. sample average), no increase or decrease is observed (e.g. Curran & Hussong, 2003). As we will discuss later on, LGMs can often be advantageous when a variable shows zero average growth over time but enough heterogeneity in change between individuals is observed (i.e. some individuals increase while others decrease).
- 2 In order to estimate the proportions of intra-individual and inter-individual variance, we calculated the intraclass correlation according to Hox (2010) using the program HLM version 6.04 (Raudenbush *et al.*, 2004).

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Edited by **ARNOLD B. BAKKER**
and **KEVIN DANIELS**



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