Longitudinal Analysis in Occupational Health Psychology: A Review and Tutorial of Three Longitudinal Modeling...

Article *in* Applied Psychology · November 2015

DOI: 10.1111/apps.12055

4 authors, including:

Yihao Liu

University of Illinois, Urbana-Champaign

Shenjiang Mo

School of Management, Zhejiang University

Yifan Song

University of Florida

APPLIED PSYCHOLOGY

APPLIED PSYCHOLOGY: AN INTERNATIONAL REVIEW, 2015, *00* (00), 00–00
doi: 10.1111/apps.12055

Longitudinal Analysis in Occupational Health Psychology: A Review and Tutorial of Three Longitudinal Modeling Techniques

Yihao Liu
University of Florida, USA

Shenjiang Mo
Sun Yat-sen University, China

Yifan Song and Mo Wang*
University of Florida, USA

There is an increasing call for the collection of longitudinal data and the use of longitudinal analysis in occupational health psychology research. Some useful and popular longitudinal analysis techniques include the cross-lagged model, the latent growth model, and the latent change score model. However, previous reviews and discussions on these modeling techniques are quite generic and often overlook the connections among these techniques. Therefore, in the current article, we first reviewed the three modeling techniques as well as their existing applications in occupational health psychology research. We then present a detailed tutorial regarding how to utilise these techniques to analyze a simulated dataset. Finally, we compare the three techniques and discuss their utility for addressing different research questions in occupational health psychology.

INTRODUCTION

Researchers in occupational health psychology (OHP) have been continuously encouraged to collect longitudinal data and conduct longitudinal analysis. For example, almost two decades ago, Zapf, Dormann, and Frese (1996) suggested that research on organisational stress should rely on longitudinal designs and various longitudinal analytic techniques, which could largely alleviate issues associated with cross-sectional data (Maxwell & Cole, 2007; Taris, 2003). More

* Address for correspondence: Mo Wang, Department of Management, University of Florida, Gainesville, FL 32611-7165, USA. Email: mo.wang@warrington.ufl.edu

recently, Kelloway and Francis (2013) emphasised again that "it is clear that longitudinal methods are increasingly necessary to explore and explain pertinent constructs and relationships in OHP" (p. 391) and briefly presented several modeling techniques to analyze longitudinal data. Consistent with these calls, recent empirical occupational health studies have identified the changing and dynamic feature of various OHP constructs and have utilised longitudinal analysis to understand the dynamics of these constructs, such as emotional labor (e.g. Hülsheger, Lang, & Maier, 2010; Gabriel & Diefendorff, in press), incivility and mistreatment (e.g. Kammeyer-Mueller, Wanberg, Rubenstein, & Song, 2013; Taylor, Bedeian, Cole, & Zhang, in press; Wang et al., 2013), physical well-being (e.g. Jones et al., in press), and stressor–strain relationships (e.g. Fuller et al., 2003; Liu, Wang, Zhan, & Shi, 2009; Meier & Spector, 2013; Wang, Liu, Zhan, & Shi, 2010).

As suggested by Ployhart and Vandenberg (2010), the primary goal of longitudinal analysis is to understand change in the variables of interest, such as how one construct changes over time and how change in one construct influences change in other constructs. This goal also applies to longitudinal analysis in OHP studies, given that "change" plays a critical part in the contributions of OHP studies, such as promoting employee mental well-being, preventing workplace accidents and injuries, and decreasing the risks of work-induced health issues (Tetrick & Quick, 2011). Despite the clear benefits of longitudinal analysis for OHP study, modeling longitudinal data could be complicated due to the large number of variables to be modeled and the various available modeling techniques. Fortunately, several groups of researchers have provided overviews and general guidelines in modeling longitudinal data with introductions to multiple longitudinal modeling techniques, among which the cross-lagged model (e.g. Burkholder & Harlow, 2003; Kelloway & Francis, 2013; Zapf et al., 1996), the latent growth model (Kelloway & Francis, 2013; Wang & Wang, 2012), and the latent change score model (e.g. Ferrer & McArdle, 2010; Kelloway & Francis, 2013; McArdle, 2001) have been identified as the three most popular techniques of modeling longitudinal data. However, previous reviews and discussions on these modeling techniques are quite generic and have a conceptual focus, without offering a detailed tutorial on how to carry out the modeling (especially for the latent change score model) in statistical software. Further, previous discussions often overlook the connections among different longitudinal data analysis techniques, failing to offer a direct comparison of the different techniques in terms of their utility. This may make it difficult for researchers to form a comprehensive understanding of longitudinal modeling techniques, limiting their ability to select the technique that best matches the research question at hand.

Therefore, in the current article, we aim to achieve two goals. First, we present how to specify longitudinal models with the above-mentioned three techniques using the same dataset as illustration. To facilitate learning and understanding for the interested reader, we also offer Mplus syntax of the three corresponding models (see Appendix) and provide interpretations of parameters in each model. Second, by discussing the advantages and disadvantages of each model, we attempt to compare the utility of the three modeling techniques and offer insights regarding how to select the modeling technique that best fits one's research question. In our discussion, we constrain the analysis to be bivariate (i.e. two constructs) for ease of illustration. All the analyses presented can be conveniently extended to accommodate a longitudinal model with three or more constructs (e.g. Selig & Preacher, 2009).

In the following sections, we first briefly summarise the three longitudinal modeling techniques (i.e. the cross-lagged model, the latent growth model, and the latent change score model) as well as their current applications in OHP studies. We then present a detailed tutorial regarding how to utilise these techniques to analyze a simulated dataset. Finally, we compare the three techniques and discuss their utility for addressing different research questions in OHP. It should be noted that other longitudinal modeling techniques exist and may be more appropriate than the currently discussed ones in dealing with special types of data (e.g. latent transition analysis and mixture latent Markov modeling in analyzing qualitative change in categorical data over time; Wang & Chan, 2011; Wang & Hanges, 2011).

OVERVIEW OF THREE LONGITUDINAL MODELING TECHNIQUES

Cross-Lagged Model

The cross-lagged model was first developed to solve issues of cross-sectional analysis, which is very limited in offering causality inference and may result in misleading parameter estimation (Maxwell & Cole, 2007; Taris, 2003). The most commonly used format of the cross-lagged model is the two-wave full panel model, in which the predictor and the outcome are both measured on the same two occasions (Kelloway & Francis, 2013). Such a model can be extended to incorporate more than two measurement occasions and include more than two constructs. For example, Figure 1 presents a cross-lagged model with two constructs X and Y measured over six time points and shows the typical specification of a cross-lagged model: each construct is specified to influence itself over time (β parameters) and to cross over to influence the other construct at a subsequent time (γ parameters), with the variance/residual variance of constructs measured at the same time set to covary (φ parameters). As such, β parameters provide information about the stability within each variable over time (also known as the "autoregressive effect") while γ

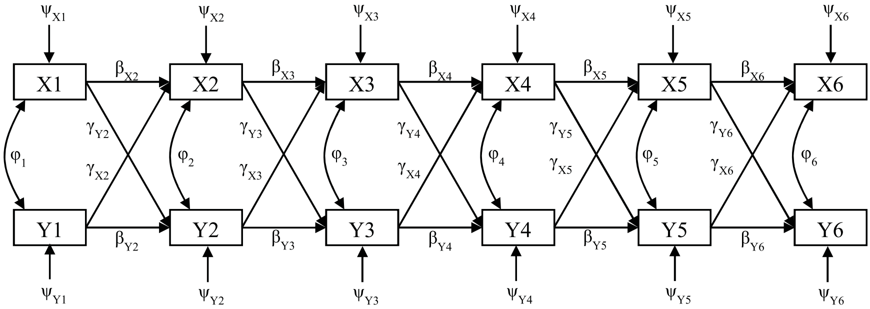


FIGURE 1. Graphic illustration of a cross-lagged model.

parameters offer information about the lagged-impact of one construct on the other construct (also known as the "cross-lagged effect"). Noting that the γ parameter indicates the lagged-impact of a predictor on an outcome beyond the outcome's own history, it can be used to enhance causal inference between different constructs (Hsiao, 2003), which explains its popularity in longitudinal analysis.

Studying the lagged impact of a predictor on an outcome beyond the outcome's own history is a very important practice in longitudinal research, because it reflects the "level-to-change" effect of a predictor at Time t on an outcome from Time t to Time t+1 and thus represents the most basic approach in modeling change (Ployhart & Vandenberg, 2010). In OHP studies, besides allowing researchers to examine change, such a "level-to-change" effect also has implications in enhancing causal inferences by offering evidence on the reversed causality hypothesis and by alleviating third variable concerns, especially in the study of "stressor–strain" relationships (Zapf et al., 1996). Note that, in longitudinal OHP studies, modeling a variable's own history is especially important for some OHP constructs such as employees' well-being, psychological distress, and substance abuse. The common feature among these constructs is that their values/states at any one time depend somewhat on the previous values/states, or in other words, they behave as if they have memory (Vancouver & Weinhardt, 2012). These constructs are usually referred to as dynamic variables. Modeling dynamic variables' own history can help researchers to obtain a more comprehensive understanding of how these variables change over time both as a function of their own internal fluctuations and as a function of external influences.

In OHP research, the cross-lagged model has gained popularity in OHP studies involving a two- or three-wave full-panel data structure. For example, using three-wave data from a sample of Dutch employees, Demerouti, Bakker, and Bulters (2004) found reciprocal relationships between work pressure, work–home interference, and employee exhaustion. Lang, Bliese, Lang, and

Adler (2011) analyzed two-wave data from three military samples and found that depressive symptoms led to subsequent organisational justice perceptions, while the opposite effects of organisational justice perceptions on depressive symptoms were not significant. Halbesleben (2010) used three-wave data from a variety of healthcare professionals and found that employee exhaustion was positively associated with safety workarounds, which were positively associated with occupational injuries. Rodríguez-Muñoz, Baillien, De Witte, Moreno-Jiménez, and Pastor (2009) used two-wave data from Belgian employees and found the unidirectional effects from workplace bullying to dedication and job-related well-being. Interestingly, very few longitudinal studies using the cross-lagged model collected data from more than three waves. Among the very few examples, Meier and Spector (2013) found the reciprocal relationships between work stressors and counterproductive work behaviors in a sample assessed five times over an eight-month period.

Generally speaking, the cross-lagged model is a useful tool for analyzing longitudinal data with two or three waves because it can enhance the causal inference by simultaneously estimating the lagged relationships between different constructs and the self-change of each construct. As such, the cross-lagged model has its values in advancing new theoretical perspectives regarding causal relations that cannot be accomplished by the traditional cross-sectional model, especially when used to test causal effects in the alternative direction. For example, the use of the cross-lagged model in OHP studies has made researchers reconsider and re-examine the well-established effects of workplace stressors on employee strains. A couple of studies utilised the cross-lagged model in analyzing longitudinal data and found that the opposite effects of employee strain on workplace stressors were also possible, which helps facilitate a more dynamic view in theorising the employee stress process (e.g. Demerouti et al., 2004; Lang et al., 2011; Meier & Spector, 2013).

However, when it comes to longitudinal data with more than three waves, the cross-lagged model becomes less favorable (compared to the latent growth model and the latent change score model), partly because of its limitation in modeling the overall change internal to each construct. For example, in Figure 1, although it is easy for us to examine the interrelationship between X and Y over time (i.e. the γ parameters), the intra-changes of X and Y themselves over time are difficult to infer. The estimation of β parameters only provides information on the self-influence of a construct from a prior measurement point, but it is unable to offer insights on how such influence accumulates over time (i.e. the overall change trajectory of a construct). Given that "change" is one of the core elements of longitudinal studies (Ployhart & Vandenberg, 2010), the major limitation of the cross-lagged model lies in its inability to describe the form and duration of change of a particular construct, especially when the construct to be modeled is inherently variable over time.

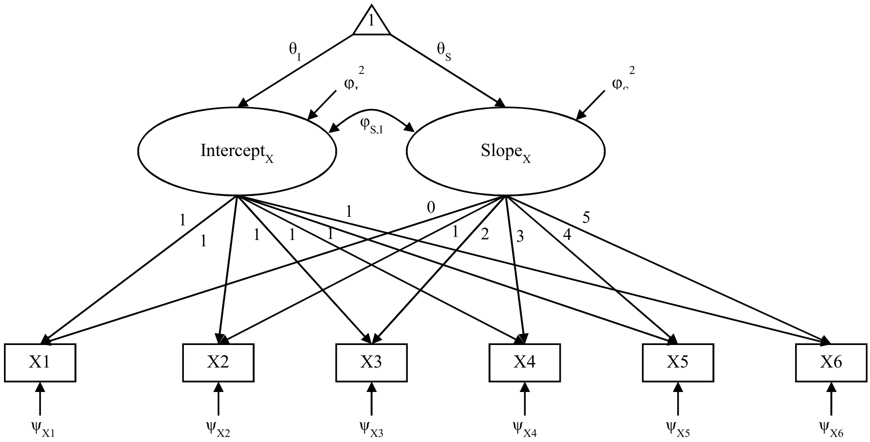


FIGURE 2. Graphic illustration of a univariate latent growth model.

Latent Growth Model

The latent growth model is usually used to assess features of change in a construct over time, such as the form of change (e.g. linear or non-linear), the rate of change, and the associations between the rate of change and the initial level of outcome (Chan, 1998; McArdle, 2009; Wang & Bodner, 2007). An example latent growth model for a single variable is shown in Figure 2, where X1–X6 are observed variables measured at six time points with an equal time interval between each consecutive two time points. To identify the latent growth trajectory, two latent factors are specified by X1–X6: an intercept factor (Intercept_X in Figure 2) that represents the initial status of X and a slope factor (Slope_X in Figure 2) that represents the rate of change of X over time. The factor loadings of the intercept factor are all set to 1.0 on the six observed variables because the intercept is a constant by definition. In contrast, the factor loadings of the slope factor are set to [0.0, 1.0, 2.0, 3.0, 4.0, 5.0] on the six observed variables to indicate a linear change trajectory. One can change the factor loadings of the slope factor on the observed indicators to estimate different forms of change trajectory, such as monotonic or piecewise change trajectories. The key information offered by the latent growth model is the parameter estimations of the two latent factors: the mean values of the intercept and the slope factors represent the magnitudes of X's initial status and rate of change, while the variances of the intercept and the slope factors indicate whether X's initial status and rate of change differ across individuals. The mean values of the intercept and the slope factors, along with the factor loadings of these two latent factors on the indicators, can be used to depict the predicted change trajectory of X over time. Specifically, if the latent slope factor has a significant mean value, one can contend that there is a potentially meaningful pattern of change in the studied variable over time, rather than some random fluctuations that do not have a clear trend. Nevertheless, to clarify the nature of the change, further theoretical and empirical probing is warranted.

When two or more variables are measured over time, one can easily extend the univariate latent growth model depicted in Figure 2 to model the latent growth curves of multiple variables, which are sometimes referred to as cross-domain latent growth models (e.g. Selig & Preacher, 2009). On the basis of the univariate latent growth model, latent growth models containing multiple variables can also estimate the relationships (covariance or directional effects) among the intercept and slope factors of the variables included. In OHP studies, such a model has been used to examine the association between changes in workplace stressors and changes in employee attitudes and behaviors. For example, Garst, Frese, and Molennar (2000) collected six-wave data from an East German sample and found that change rates of workplace stressors (i.e. slope factors of social stressors, role ambiguity, and conflict) were positively related to change rates of employee strains (i.e. slope factors of depression, psychosomatic complaints). Using three-wave nationally representative data of Canadian employees, Christie and Barling (2009) estimated the cross effects of intercept factors of personal control and workplace stressors on each other's slope factors. They found that employees who initially had higher levels of personal control experienced increasingly fewer workplace stressors over time and employees who initially underwent higher levels of workplace stressors increasingly perceived less personal control over time. Vandenberghe, Panaccio, Bentein, Mignonac, and Roussel (2011) sampled a group of newcomers in a three-wave design and found that an increase in newcomers' role overload and role conflict was associated with a decline in affective commitment and job satisfaction, respectively.

Compared to the cross-lagged model which can also model the interrelationship between multiple constructs over time, the most salient advantage of the multivariate latent growth model is that it can reveal the respective change trajectory of each construct over time as well as the general associations among the changes in different constructs (Ferrer & McArdle, 2010). In addition, compared to the cross-lagged model, the latent growth model is more flexible in accounting for individual differences in the changes of the studied variables (Kelloway & Francis, 2013). For example, both time-varying and time-invariant covariates can be included in the latent growth model, depending on the specific research questions. However, the latent growth model is not as good as the cross-lagged model in establishing causal inference (Ferrer & McArdle, 2010). Specifically, when two latent growth curves are modeled simultaneously, neither the "intercept–intercept" covariance nor the "slope–slope" covariance can be used to make a strong causal inference if the measurement windows of the two variables have overlaps. The "intercept–slope"

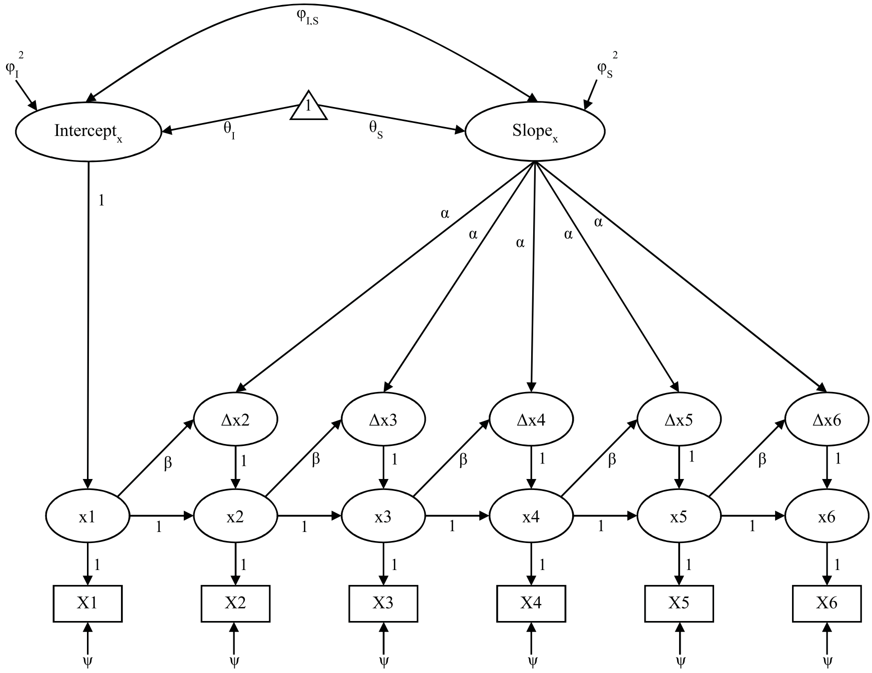


FIGURE 3. Graphic illustration of a univariate latent change score model.

covariance between two constructs offers a clearer causal direction, but its theoretical meaning is limited because it cannot tell whether the changing trends of the two variables influence each other in a causal manner.

Latent Change Score Model

Recently, the latent change score model (also known as the latent difference score model) has started to receive recognition from organisational researchers in analyzing longitudinal data (e.g. Halbesleben & Wheeler, 2015; Jones et al., in press; Li, Fay, Frese, Harms, & Gao, 2014; Smith, Amiot, Smith, Callan, & Terry, 2013; Taylor et al., in press). Figure 3 presents an example of the univariate latent change score model, which includes repeated measures of observed variable X at six time points (i.e. X1–X6). The repeated measures of X are then represented as the latent variables x1–x6. One unique feature of the latent change score model is that it specifies a variable's change score between two adjacent measurement occasions represented by a distinct latent factor (i.e. latent change score Δx2–Δx6 in Figure 3). Besides, similar to the latent growth model, the latent change score model also explicitly specifies the change trajectory represented by the latent intercept and slope factors (Intercept_x and Slope_x in Figure 3). In this way, each x variable at time t can be written as a function of the sum of two components: x at a previous time and change in x.

$$x_{t+1} = x_t + \Delta x_{t+1} \tag{1}$$

The change in x, then, can be expressed as:

$$\Delta x_{t+1} = \beta x_t + \alpha\theta_S \tag{2}$$

On the one hand, β represents the proportional change of Δx from a previous time point to the subsequent time point and is also known as the proportional change parameter. This is because simple algebra using formula (1), formula (2), and the following formula

$$\Delta x_{t+2} = \beta x_{t+1} + \alpha\theta_S \tag{3}$$

will lead to:

$$\beta = (\Delta x_{t+2} - \Delta x_{t+1})/\Delta x_{t+1} \tag{4}$$

that is, β equals the proportional change of two adjacent latent change scores of x. On the other hand, α represents the constant change from the linear slope over the time series and carries the influence of the latent slope's mean (θ_S) onto each latent change score (McArdle, 2001, 2009). In this way, the change in latent variable x over time can be termed a dual-change process—a systematic constant change (α) and a systematic proportional change over time (β). For simplicity of model specification, one can impose equality constrains on α parameters and β parameters, respectively (McArdle, 2009; Selig & Preacher, 2009). Noting that even equality constraints are imposed on α and β parameters over time, this does not mean that we constrain the changing trajectory to be linear because β parameter will carry over and accumulate influences of x over time and will exhibit an exponentially changing trend in the latent change scores. One can of course remove the equality constraints on α and β parameters in specifying the latent change score model, but model comparisons between unconstrained and constrained models are necessary to determine the model that best fits the data.

Practically, one can use the following procedures to specify a univariate latent change score model. First, the latent score of each X variable is created by loading each X variable on its respective latent variable (i.e. x1–x6) with a fixed factor loading of 1.0. Second, the autoregressive effects are specified with a fixed value of 1.0 between x1 and x2, x2 and x3, and so on. Third, the latent change score (i.e. Δx2–Δx6) at each time point (excluding T1) is specified as a latent cause of the latent x variable at that time point with a fixed factor loading at 1.0. Fourth, the path from each latent x variable on the latent change score at a subsequent time point is specified and freely estimated (i.e. β parameters). Equality constraints can be imposed on β parameters depending on the specific research question. Fifth, a latent intercept factor is created as indicated by x1 with a fixed factor loading at 1.0. Sixth, a latent slope factor is specified as a latent cause of all latent change scores with factor loadings representing α parameters. Equality constraints can be imposed on α parameters, which means all α parameters are fixed to 1.0 and renders θ_S to represent a constant change component in Δx over time. As a final step, the means of X1–X6, x1–x6, and Δx2–Δx6, as well as the residual variances of x1–x6 and Δx2–Δx6, are all fixed to zero. Further, residuals of X1–X6 are set to be equal, indicating stable measurement error variance over time. Interested readers can refer to McArdle (2001, 2009) and Ferrer and McArdle (2010) for more technical details of model specification.

The latent change score model has two major advantages over the cross-lagged model and the latent growth model. First, the latent change score model can be used to model the associations between changes between multiple constructs by estimating different forms of dynamic effects, including the effect of current levels of one variable on the subsequent changes in another variable (i.e. the “level-to-change” effect) and the effect of current changes in one variable on the subsequent changes in another variable (i.e. the “change-to-change” effect). Similar to the cross-lagged model, this enables researchers to enhance the causal inference in examining the relationships between various constructs. Moreover, because the latent change score model allows examinations of different forms of causal relationships, it can provide a more nuanced perspective in the development of OHP theories by revealing the most appropriate form of causal relationships among constructs. For example, Taylor et al. (in press) found that incivility change uniquely affected subsequent changes in employee burnout, which in turn led to subsequent changes in turnover cognitions. Such relationships did not emerge among the absolute levels of incivility, burnout, and turnover cognitions, which indicates the relative nature of workplace incivility and highlights the role of employees’ previously perceived workplace incivility in determining the consequences of workplace incivility.

Second, the latent change score model also offers information necessary to the examination of constructs’ general changing trends over time. Specifically, by estimating the constant change parameter α, the proportional change parameter β, and the mean values of the latent intercept and slope factors, it is plausible to derive the predicted value of the latent variable measured at each time point and plot out the average changing trajectory with the sample. For example, the estimated mean value of the intercept factor (i.e. θ_I) represents the predicted value at T1 (i.e. $\hat{x}1$). The predicted value at T2 (i.e. $\hat{x}2$) can be expressed as $\hat{x}1 + \Delta\hat{x}2$, where $\Delta\hat{x}2$ equals $\beta\hat{x}1 + \alpha\theta_S$, and so on. It can also reveal the general associations among the changes in constructs by estimating the covariances among intercept and slope factors of different constructs. Therefore, the latent change score model has the most distinct advantage over the latent growth model.

As pointed out by Ferrer and McArdle (2010), the cross-lagged model "... could have identified influences across the different variables over time but without capturing the patterns of growth and decline", while the latent growth model "... would have revealed the general associations among the changes of the different variables but without information about which lead and which lag in such longitudinal relationships" (p. 150). As such, we believe that the latent change score model has the advantages of both the cross-lagged model and the latent growth model and at the same time avoids the disadvantages of these two techniques.

In fact, as proposed by McArdle and Ferrer (Ferrer & McArdle, 2003, 2010; McArdle, 2009), the latent change score model can be seen as a global framework for the study of change in longitudinal studies due to the features discussed above. In particular, the inclusion of the latent change score factors serve as a "bridge" that connects two levels of change: the local self-change between two adjacent time points (represented by β parameters) and the overall change trajectory across the whole time window (represented by α parameters and the latent intercept and slope factors). Moreover, the latent change score model has great flexibility in its parameterisation and allows researchers to impose equality or inequality constraints on α and/or β parameters across time as needed, which makes it possible to model and compare changes in different forms in a more economical way. In other words, the cross-lagged model and the latent growth curve model can be treated as two special cases of the latent change score model with certain sets of parameter specifications. It is also interesting to point out that the latent change score model is not the only global framework of longitudinal analysis. Rovine and Molenaar (2005) also developed a global framework for analyzing longitudinal data called the nonstationary autoregressive moving average (NARMA) framework. In this framework, changes in a repeatedly measured variable are described using two quasi-simplex processes: an autoregressive (AR) process and a moving average (MA) process. Any longitudinal model with continuous indicators and continuous latent variables can be rewritten in a certain combination of an AR process and an MA process. For example, a linear latent growth model can be represented as an NAMRA(2, 1) model, which includes a second-order AR process and a first-order MA process. Discussion of this time series-based framework falls out side the scope of the current paper. Interested readers could read DeShon (2012) for an introduction to modeling this type of dynamics in organisational science.

A few other OHP studies have utilised this technique in examining the association between changes in variables over time. For example, Jones et al.

(in press) surveyed a sample of pregnant employees over the course of pregnancy and found that how pregnant workers chose to manage their pregnant identities influenced the changes in their physical health while changes in the decision about revealing pregnancy were also partly based on their physical health conditions. Toker and Biron (2012) used a simplified version of the latent change score model (i.e. not controlling for the time change trend represented by the latent intercept and slope factors) and found a reciprocal relationship between changes in depression and changes in job burnout, such that an increase in depression predicted an increase in job burnout at a subsequent time and vice versa.

DEMONSTRATION WITH A SIMULATED DATA SET

Simulated Data

In this section, we use a simulated dataset to demonstrate how to model longitudinal data with the three techniques discussed. All models were fitted in the Mplus 7.0 software (Muthén & Muthén, 1998–2012) and the selected model syntax can be found in the Appendix. Data were also simulated in the Mplus 7.0 software (Muthén & Muthén, 1998–2012). Specifically, 12 variables were created, with six variables indicating variable Xs measured from Time 1 to Time 6 (labeled X1, X2, X3, X4, X5 and X6) and another six variables indicating variable Ys measured from Time 1 to Time 6 (labeled Y1, Y2, Y3, Y4, Y5, and Y6). The number of cases in the sample was set to 500. The time intervals between two adjacent measurement occasions were assumed to be equal. The correlation matrix of the simulated variables, along with their means and standard deviations, are presented in Table 1. Interested readers can request the dataset and the simulation specifications from the first author.

Cross-Lagged Model

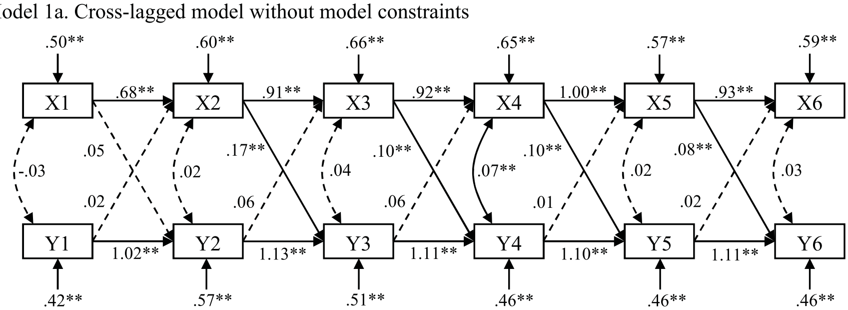
We first fitted a cross-lagged model without any coefficient constraints (see Model 1a in Figure 4). In Model 1a, the autoregressive effects of X (i.e. $X_t \rightarrow X_{t+1}$) and Y (i.e. $Y_t \rightarrow Y_{t+1}$), the cross-lagged effects of X (i.e. $X_t \rightarrow Y_{t+1}$) and Y (i.e. $Y_t \rightarrow X_{t+1}$), the covariance between X and Y measured at the same time point, and the residuals of X and Y were all freely estimated. The upper panel of Figure 4 summarises the unstandardised coefficients estimated in Model 1a. Note that in Model 1a the cross-lagged effects of Y_t on X_{t+1} were not significant across all time lags (γs = .01~.06, ps > .05), whereas the cross-lagged effects of X_t on Y_{t+1} were significant across four out of the five time lags (γs = .08~.17, ps < .01; the only non-significant cross-lagged effect occurred at the lag from T1 to T2, $\gamma = .05$, $p > .05$). These results suggest that the

TABLE 1
Means, Standard Deviations, and Correlations among Simulated Variables

Variables	M	SD	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*Y1*	*Y2*	*Y3*	*Y4*	*Y5*
X1	.80	.71											
X2	1.14	.91	.53										
X3	1.38	1.17	.54	.71									
X4	1.66	1.35	.58	.75	.80								
X5	1.81	1.55	.59	.76	.83	.87							
X6	1.97	1.64	.58	.76	.84	.88	.88						
Y1	.35	.65	−.07	−.02	.01	.03	−.01	.00					
Y2	.89	1.00	−.01	.02	.06	.09	.07	.06	.66				
Y3	1.56	1.35	− .52	.13	.16	.18	.16	.16	.69	.84			
Y4	2.18	1.67	.11	.19	.22	.25	.23	.24	.70	.85	.91		
Y5	2.75	2.00	.13	.23	.26	.30	.28	.27	.70	.86	.91	.94	
Y6	3.27	2.35	.15	.25	.29	.33	.31	.31	.69	.85	.92	.94	.96

Notes: $N = 500$. Correlations with values higher than .08 were significant at the .05 level and higher than .13 were significant at the .01 level.

Model 1a. Cross-lagged model without model constraints



Model 1b. Cross-lagged model with model constraints on auto-regressive and cross-lagged effects

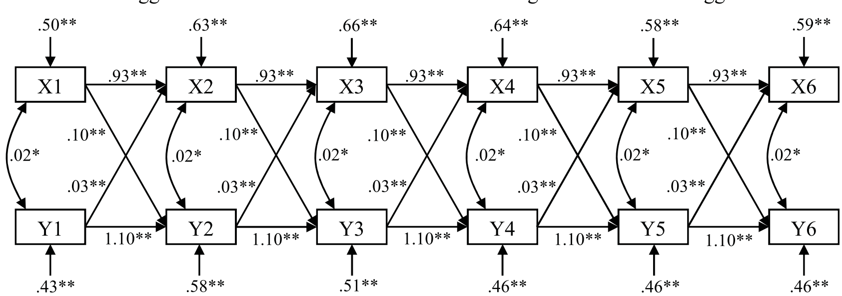


FIGURE 4. Unstandardised coefficients of the cross-lagged models.
Notes: * $p < .05$; ** $p < .01$. Complete outputs of model estimation are available upon request.

relationships between X and Y may not be reciprocal in nature. Instead, the causal direction is more likely to flow from X to Y rather than from Y to X.

Previous OHP studies have sometimes imposed equality constraints on the autoregressive and/or cross-lagged coefficients when fitting cross-lagged models (e.g. Meier & Spector, 2013). By comparing cross-lagged models with and without constraints, researchers hope to determine whether the autoregressive/cross-lagged effects are subject to change over time, which is often difficult to theorise a priori. Although this practice is useful in examining changes in the autoregressive and cross-lagged effects over time, one should be careful because adding additional constraints on models may generate new issues with parameter estimations, especially when the cross-lagged model includes variables measured over multiple times (e.g. more than three times). For instance, on the basis of Model 1a, we fitted Model 1b which had an equal autoregressive effect and equal cross-lagged effect for X and Y, respectively, and had equal covariance between X and Y measured at the same time over time. The lower panel of Figure 4 summarises the unstandardised coefficients estimated for Model 1b. An interesting finding is that, in contrast to the unidirectional effect of X on Y over time, Model 1b reveals a reciprocal relationship between X and Y over time ($\gamma = .10$, $p < .01$ from X to Y, and $\gamma = .03$, $p < .01$ from Y to X). Although the model comparison test showed a preference for Model 1a (χ^2 [$df = 40$] = 1081.13, $p < .01$) over Model 1b (χ^2 [$df = 61$] = 1135.72, $p < .01$; $\Delta\chi^2$ [$\Delta df = 21$] = 54.59, $p < .01$), the inconsistency between parameter estimates of causal effects in Model 1a and Model 1b is still surprising. Indeed, one can draw completely different conclusions from the two sets of findings. Although it is difficult to fully interpret such findings, it at least suggests that cross-lagged analysis may have its inherent limitations in modeling multivariate relationships across more than three time points and that future research should be cautious in using cross-lagged analysis.

Latent Growth Model

Next, we fit a set of latent growth models to the simulated data. To begin with, we specified and evaluated the fit of three possible latent growth models for X and Y, respectively, including the linear growth model, the freely-estimated growth model, and the quadratic growth model. In all three models for X variables, X1–X6 were loaded on the intercept factor with factor loadings of 1.0. For the linear growth model (Model 2ax), the factor loadings from X1 to X6 on the slope factor were fixed as [0.0, 1.0, 2.0, 3.0, 4.0, 5.0], representing a linear change trend. On the basis of Model 2ax, the freely-estimated growth model (Model 2bx) was fitted by freely estimating the factor loadings of X3, X4, X5, and X6, which helped to detect how much the latent growth deviated from the linear change trend. We further considered the possibility that the

TABLE 2
Model Comparisons of Latent Growth Models for X and Y Variables

Model	*AIC*	*BIC*	*SSBIC*	χ^2	df	*RMSEA*	*CFI*	*TLI*	*SRMR*
X variables									
Model 2ax	6552.65	6599.01	6564.09	82.10	16	.09	.98	.98	.05
Model 2bx	6489.76	6552.98	6505.37	11.21	12	.00	1.00	1.00	.01
Model 2cx	*6488.01*	*6551.25*	*6503.64*	*9.48*	*12*	*.00*	*1.00*	*1.00*	*.02*
Y variables									
Model 2ay	6004.80	6051.16	6016.24	41.00	16	.06	.99	1.00	.03
Model 2by	*5990.68*	*6053.89*	*6006.28*	*18.88*	*12*	*.03*	*1.00*	*1.00*	*.03*
Model 2cy	5994.49	6057.71	6010.10	22.70	12	.04	1.00	1.00	.02

Notes: $N = 500$. Models with the best model fit are in italics. Model 2ax = linear growth model for X, Model 2bx = freely-estimated growth model for X, Model 2cx = quadratic growth model for X, Model 2ay = linear growth model for Y, Model 2by = freely-estimated growth model for Y, and Model 2cy = quadratic growth model for Y. AIC = Akaike information criterion, BIC = Bayes information criterion, SSBIC = Sample-size adjusted Bayesian information criterion, χ^2 = chi-square, CFI = Comparative fit index, TLI = Tucker-Lewis index, RMSEA = Root mean square error of approximation, SRMR = Standardised root mean square residual.

latent growth model exhibited a quadratic trend. Therefore, on the basis of Model 2ax, we fitted a quadratic growth model (Model 2cx) by adding a quadratic slope factor with factor loadings fixed as [0.0, 1.0, 4.0, 9.0, 16.0, 25.0] for X1 to X6. The same specifications were also applied to the three latent growth models for Y variables (i.e. Model 2ay represents the linear growth model, Model 2by represents the freely-estimated growth model, and Model 2cy represents the quadratic growth model).

Table 2 summarises the unstandardised model coefficients estimated for the six latent growth models as specified above. For nested models (i.e. the linear growth model vs. the freely-estimated model), model fit was evaluated based on the chi-square statistic, the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardised root mean square residual (SRMR). For non-nested models (i.e. the linear growth model vs. the quadratic growth model, the freely-estimated model vs. the quadratic growth model), information criteria, such as the Akaike information criterion (AIC), Bayes information criterion (BIC), and sample-size adjusted Bayesian information criterion (SSBIC), were used to evaluate model fit (lower information criteria indicate better model fit). Model comparisons revealed that the quadratic growth model (mean of intercept factor = .80, mean of slope factor = .35, and mean of quadratic slope factor = −.02, ps < .01) fitted the change in X variables best and the freely-estimated growth model (mean of intercept factor = .34 and mean of slope factor = .57, ps < .01; estimated factor loadings of the slope factor was .00,

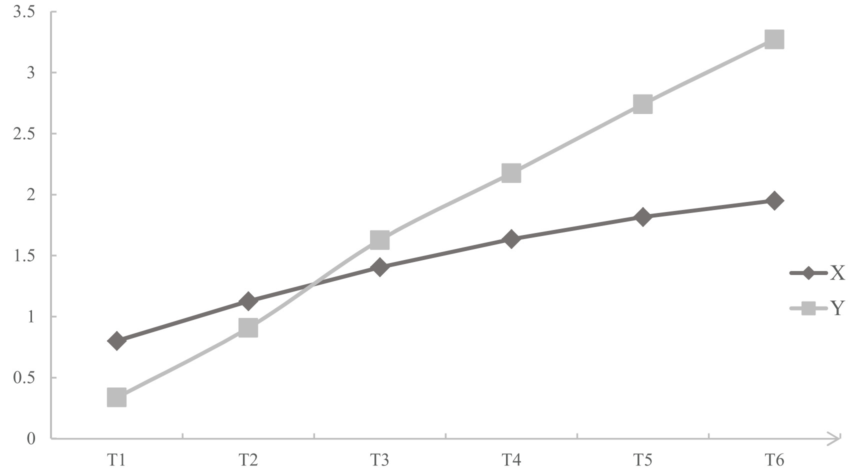


FIGURE 5. Best fitting growth curves for X and Y variables.

1.00, 2.16, 3.22, 4.21, and 5.14 on Y1–Y6, respectively) fitted the change in Y variables best. Figure 5 depicts the estimated growth curves for these two best-fitting models and show that both X and Y variables followed an overall increasing trajectory with a decreasing change rate.

As a final step, we fitted the two best-fitting models simultaneously and allowed all latent factors to correlate with each other (Model 2d), the unstandardised solution of which is depicted in Figure 6. As shown in Figure 6, the initial status of X was negatively correlated with the initial status of Y ($r = -.06$, $p < .01$) but positively correlated with the change rate of Y ($r = .05$, $p < .01$). This suggests that individuals with a higher starting value of X tend to have a lower starting value of Y while having a faster rate of change in Y over time. In addition, the rate of change in Y was positively correlated with the linear change rate of X ($r = .07$, $p < .01$) but negatively correlated with the quadratic change rate of X ($r = -.01$, $p < .01$), suggesting that individuals with a faster rate of change in Y over time are also likely to have a faster linear rate of change in X and a lower quadratic rate of change in X over time.

Latent Change Score Model

Finally, we fitted a bivariate latent change score model (Model 3a) with the simulated data. We first fitted the univariate latent change score model for X and Y variables, respectively. Then on the basis of the two univariate latent change score models, we made further specifications to build the bivariate latent change score model. We first specified the effects of the prior level of

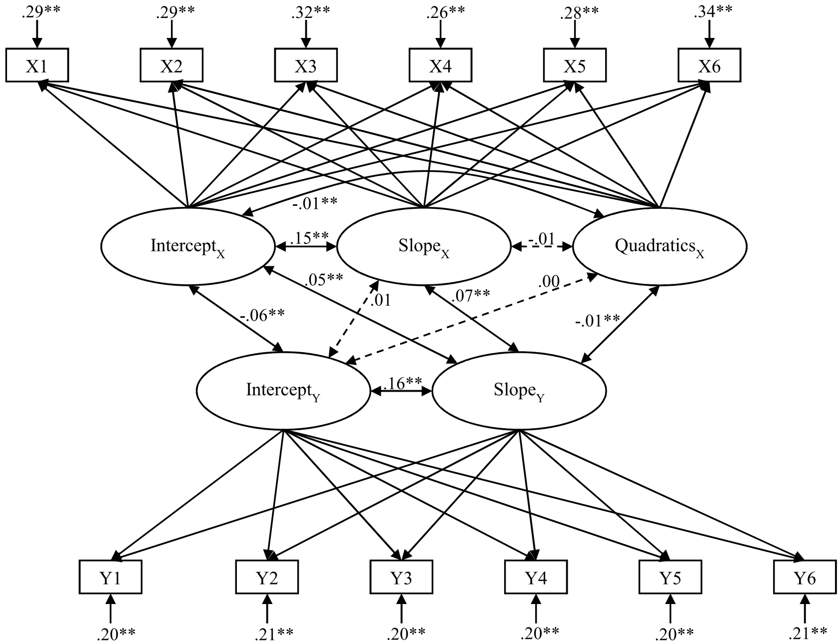


FIGURE 6. Unstandardised coefficients of the bivariate latent growth model between X and Y variables (Model 2d).
Notes: ** $p < .01$. The factor loadings of Intercept_X were all set as 1 on X1–X6. The factor loadings of Slope_X were set as [0, 1, 2, 3, 4, 5] on X1–X6. The factor loadings of Quadratics_X were set as [0, 1, 4, 9, 16, 25] on X1–X6. The factor loadings of Intercept_Y were all set as 1 on Y1–Y6. The factor loadings of Slope_Y were set as [0, 1, 2.26, 3.22, 4.21, 5.14] on Y1–Y6. Complete outputs of model estimation are available upon request.

variable x/variable y (i.e. x_t/y_t) on the latent change score of variable y/variable x at a subsequent occasion (i.e. $\Delta y_{t+1}/\Delta x_{t+1}$). These parameters are usually referred to as coupling parameters or level-to-change effects (Grimm, 2007; Taylor et al., in press) and are represented by γ_{yx} (i.e. regressing Δy_{t+1} on x_t) and γ_{xy} (i.e. regressing Δx_{t+1} on y_t). Then we specified the effects of a prior latent change score of variable x/variable y (i.e. $\Delta x_t/\Delta y_t$) on the latent change score of variable y/variable x at a subsequent occasion (i.e. $\Delta y_{t+1}/\Delta x_{t+1}$). These parameters are usually referred to as change-to-change parameters (Taylor et al., in press) and are represented by ζ_{yx} (i.e. regressing Δy_{t+1} on Δx_t) and ζ_{xy} (i.e. regressing Δx_{t+1} on Δy_t). Following the tradition of latent change score model specification (e.g. Jones et al., in press; Taylor et al., in press), γ_{yx}, γ_{xy}, ζ_{yx}, and ζ_{xy} were all set to be equal across different time points, respectively (i.e. both the level-to-change effects and change-to-change effects are stable over

TABLE 3
Comparisons of Model 3a and Alternative Latent Change Score Models

Model	χ^2	df	$\Delta\chi^2$	Δdf	*Sig.*
Model 3a: the original bivariate latent change score models used as baseline of model comparison	52.25	68			
Model 3b: on the basis of Model 3a, the constraints of fixing all α parameters were relaxed	51.66	66	.59	2	$p > .05$
Model 3c: on the basis of Model 3a, the equality constraints on β parameters were relaxed for both X and Y variables	49.90	60	2.35	8	$p > .05$
Model 3d: on the basis of Model 3a, the equality constraints on residual variance of observed variables were relaxed for both X and Y variables	48.26	58	3.99	10	$p > .05$
Model 3e: on the basis of Model 3a, the equality constraints on γ parameters were relaxed for both X and Y variables	43.26	60	8.99	8	$p > .05$
Model 3f: on the basis of Model 3a, the equality constraints on ζ parameters were relaxed for both X and Y variables	47.84	62	4.41	6	$p > .05$

Notes: $N = 500$. $\Delta\chi^2$ was calculated as the difference between χ^2 of Model 3a and of each alternative model. Δdf was calculated as the difference between df of Model 3a and of each alternative model. "Sig" represents the p-value associated with the significant test of $\Delta\chi^2$ with Δdf. A non-significant p-value means that model fit of the alternative model did not significantly improve compared to Model 3a.

time). Finally, we allowed the four latent intercept and slope factors specified earlier to freely covary with one another.

In the above model (i.e. Model 3a), we imposed multiple parameter constraints. For example, we constrained all α parameters to be 1.0, constrained β parameters to be equal for X and Y variables, respectively, constrained the residual variances of X and Y variables to be equal, respectively, constrained γ parameters to be equal for X and Y variables, respectively, and constrained ζ parameters to be equal for X and Y variables, respectively. To determine whether Model 3a was the best-fitting model with the best parsimony, we compared Model 3a with various alternative models with only partial parameter constraints. Table 3 lists how the alternative models were specified and summarises the results of model comparisons with Model 3a. As shown in Table 3, Model 3a, the most parsimonious model, did not fit the data worse than any of the listed alternative models with one of the parameter constraints relaxed.

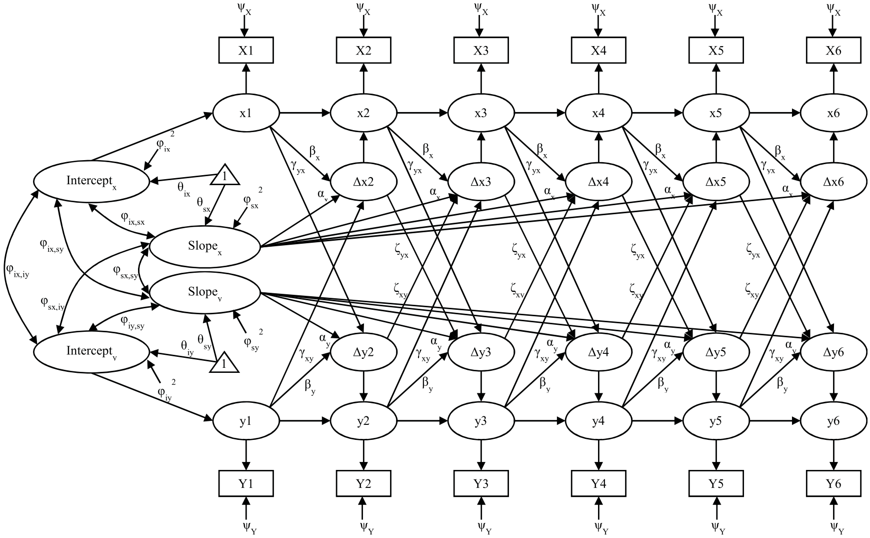


FIGURE 7. Graphic illustration of the bivariate latent change score model (Model 3a).
Notes: Unlabeled paths were fixed to 1 while labeled paths were constrained to equality. Except that α_x and α_y paths were fixed at 1, all other labeled paths were freely estimated. Unlabeled variance and mean components were fixed to 0.

Therefore, Model 3a was preferred over all the alternative models. A rough overview of previous OHP studies, though, reveals that most of these studies did not test these alternative models with relaxed parameter constraints but usually instead imposed various model constraints with little justification. Given the complexity of latent change score models, we understand that parameter constraints may have to be imposed to achieve model convergence. However, this practice may lead to failures in detecting the true dynamics over the change in one or more variables, such as different proportional changes over time (i.e. unequal β parameters) in a univariate latent change score model and changing coupling effects from one variable to another variable over time (i.e. unequal γ parameters) in a bivariate latent change score model. Therefore, we strongly suggest that future research comprehensively evaluating the necessity for imposing parameter constraints when estimating latent change score models.

Figure 7 illustrates how the bivariate latent change score model (i.e. Model 3a) was created and summarises how model parameters were specified. Despite the model complexity, among all the specified path parameters, only β, γ, ζ, and θ parameters were set as free parameters (parameter constraints applied). These three parameters, plus the fixed α parameters, will be used to determine

TABLE 4
Unstandardised Coefficients for the Bivariate Latent Change Score Model (Model 3a)

	Δx_{i+1}			Δy_{i+1}	
	Estimate	SE		*Estimate*	SE
Predictors			Predictors		
x_i (β_x path)	−.16**	.03	y_i (β_y path)	−.08**	.02
y_i (γ_{xy} path)	−.02	.02	x_i (γ_{yx} path)	.11**	.03
Δy_i (ζ_{xy} path)	.02	.06	Δx_i (ζ_{yx} path)	.33**	.09
Mean components			Mean components		
Intercept_x (θ_{ix})	.79**	.03	Intercept_y (θ_{iy})	.35**	.03
Slope_x (θ_{sx})	.47**	.04	Slope_y (θ_{sy})	.49**	.03
Variance components			Variance components		
X_i (ψ_X)	.29**	.01	Y_i (ψ_Y)	.20**	.01
Intercept_x ($\varphi_{ix}{}^2$)	.21**	.03	Intercept_y ($\varphi_{iy}{}^2$)	.24**	.02
Slope_x ($\varphi_{sx}{}^2$)	.15**	.02	Slope_y ($\varphi_{sy}{}^2$)	.18**	.02

Notes: $N = 500$. i represents an integral number ranging from 1 to 5. Covariances among latent intercept and slope factors were estimated but are not presented in the table: $\varphi_{ix,sx} = .17$**, *S.E.* = .02; $\varphi_{ix,iy} = -.02$, *SE* = .02; $\varphi_{ix,sy} = -.01$, *SE* = .02; $\varphi_{sx,iy} = .01$, *SE* = .02; $\varphi_{sx,sy} = .01$, *SE* = .02; $\varphi_{iy,sy} = .21$**, *SE* = .02. 24 ***p* < .01.

the univariate and bivariate dynamics of the studied variables over time (McArdle, 2009). Table 4 presents the unstandardised estimations of these parameters, along with mean and variance components estimated for Model 3a. As shown in Table 4, neither γ_{xy} (−.02, $p > .05$) nor ζ_{xy} (.02, $p > .05$) was significant, suggesting that change in X variables was neither influenced by the level nor by the change in Y variables. Nevertheless, Table 4 shows that both γ_{yx} (.11, $p < .01$) and ζ_{yx} (.33, $p < .01$) were significant, suggesting that (a) a higher level of X at a prior time point (e.g. T1) could lead to a large change in Y from that time point to the subsequent time point (e.g. T1 to T2), and (b) a larger change in X from a prior time point to a subsequent time point (e.g. T1 to T2) could lead to a larger change in Y during the subsequent time period (e.g. T2 to T3). In other words, estimations of γ and ζ parameters reveal that the causal direction between X and Y is more likely to flow from X to Y, rather than the other way around. Such a causal relationship could be displayed in two forms: a level-to-change relationship from X to Y and a change-to-change relationship from X to Y.

As shown in Table 4, both X variables ($\beta_x = -.16$, $p < .01$) and Y variables ($\beta_y = -.08$, $p < .01$) had a negative and significant β path coefficient. This parameter represents the average rate of change in the *change* of a variable from a previous change occasion (e.g. Δx2, or x1 → x2) to a subsequent change occasion (e.g. Δx3, or x2 → x3). However, β parameter by itself is not adequate

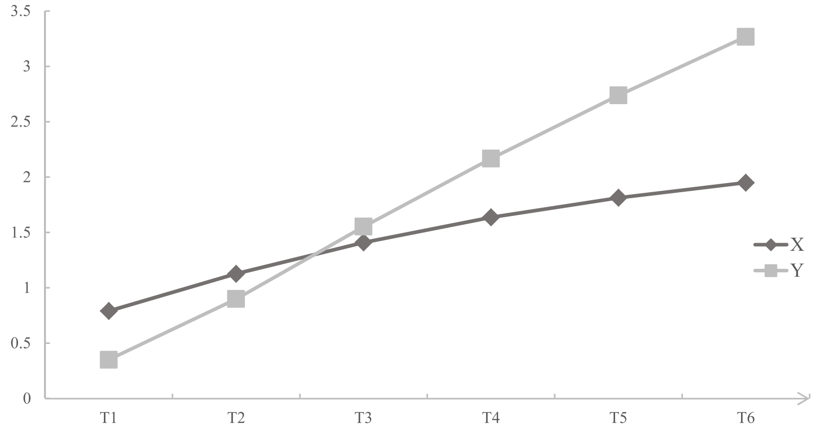


FIGURE 8. Growth curves for X and Y variables using predicted values derived from Model 3a.

to determine the changing trajectory of a variable. To determine the predicted values of X and Y variables at each time point, information on α parameters, β parameters, γ parameters, ζ parameters, and the mean value of the slope factor (θ_s) and the intercept factor (θ_i) are combined together to generate the predicted values. For instance, the predicted value of the X variable at T1 (i.e. $\hat{x}1$) will be the estimated mean value of the intercept factor of X (i.e. θ_{ix}). The predicted value of the Y variable at T1 (i.e. $\hat{y}1$) will be the estimated mean value of the intercept factor of Y (i.e. θ_{iy}). The predicted value of the X variable at T2 (i.e. $\hat{x}2$) will be expressed as $\hat{x}1 + \Delta\hat{x}2$, where $\Delta\hat{x}2$ equals $\beta_x\hat{x}1 + \alpha_x\theta_{sx} + \gamma_{xy}\hat{y}1$. The predicted value of the Y variable at T2 (i.e. $\hat{y}2$) will be expressed as $\hat{y}1 + \Delta\hat{y}2$, where $\Delta\hat{y}2$ equals $\beta_y\hat{y}1 + \alpha_y\theta_{sy} + \gamma_{yx}\hat{x}1$. The predicted value of the X variable at T3 (i.e. $\hat{x}3$) will be expressed as $\hat{x}2 + \Delta\hat{x}3$, where $\Delta\hat{x}3$ equals $\beta_x\hat{x}2 + \alpha_x\theta_{sx} + \gamma_{xy}\hat{y}2 + \zeta_{xy}\Delta\hat{y}2$. The predicted value of the Y variable at T3 (i.e. $\hat{y}3$) will be expressed as $\hat{y}2 + \Delta\hat{y}3$, where $\Delta\hat{y}3$ equals $\beta_y\hat{y}2 + \alpha_y\theta_{sy} + \gamma_{yx}\hat{x}2 + \zeta_{yx}\Delta\hat{x}2$, and so on. Following these formulas, Figure 8 depicts the trajectories of X and Y with the predicted values of X and Y across the six measurement points.

DISCUSSION

In this article, we have given an overview of three popular analytic techniques for modeling longitudinal data and have provided empirical demonstrations on how to implement these techniques in data analysis. The purpose of the current article is to offer a comprehensive comparison of these popular techniques in terms of their conceptualisation, operationalisation, and the theoretical inferences that can be drawn from their resulting findings. In this section, we further discuss the advantages and disadvantages of each technique from three aspects—causal inference, change description, and issues of modeling and interpretation. We conclude this article with recommendations on longitudinal analysis for future OHP studies.

Before we discuss the three specific techniques covered in this paper, it is worth noting that these three techniques are not exhaustive among the techniques of longitudinal analysis. For example, Bollen and Curran (2004; also see Curran & Bollen, 2001) developed an autoregressive latent trajectory model as a synthesis of the autoregressive model and the latent growth model in an effort to provide "... a model of change that recognizes both individual trajectories as well as the effect of earlier values in determining the course of repeated measures" (Bollen & Curran, 2004, p. 378). In an autoregressive latent trajectory model, both the latent intercept and the latent slope factors are specified to represent the latent growth trajectory of the studied variables over time. In addition, the autoregressive effects are also specified between variables measured at two adjacent time points. The autoregressive latent trajectory model and the latent change score model share a few common features, especially in their abilities to describe change and to account for the variables' own history. However, the latent change score model has some unique features that cannot be arrived at through the autoregressive latent trajectory model, such as the ability to flexibly model non-linear change trajectories and to disentangle the change-to-change effect from the level-to-change effect. Moreover, compared to the growing application of the latent change score model, the application of the autoregressive latent trajectory model is still very rare in the OHP literature and in the broader organisational psychology literature (for exceptions, see Judge, Simon, Hurst, & Kelly, 2014; Zyphur, Chaturvedi, & Arvey, 2008). Therefore, we do not include a discussion of the autoregressive latent trajectory model as a major technique in analyzing longitudinal data for OHP studies.

Causal Inference

Although establishing and enhancing causal inference is one of the most important tasks for researchers in understanding the relationships and dynamics between different constructs, the existing empirical organisational research, including OHP research, is rarely able to fully reveal the causal relations among the studied phenomena through research designs and analyses as noticed by many researchers (e.g. Bentein, Vandenberghe, Vandenberg, & Stinglhamber, 2005; Chan, 1998, 2011; Ployhart & Vandenberg, 2010). As a bottom line, the time separation between the constructs studied should be considered in designing research that aims to establish causal relationships, because the condition "cause must precede the effect" (James, Mulaik, & Brett, 1982; Condition 3 of 10 for inferring causality, p. 36) is at the heart of causality inference.

As such, analyzing longitudinal data involving variables measured at several different time points is valuable in enhancing causality inference, especially with the cross-lagged model and the latent change score model. In particular, as we demonstrated earlier with the simulated data, both the cross-lagged model and the latent change score model revealed that the dynamics between X and Y were unidirectional, flowing from X to Y rather than from Y to X. Moreover, this causal relationship from X to Y showed adequate consistency in terms of both valence (i.e. positive) and magnitude (i.e. around .10 in both models) over time, especially from Time 2 to Time 6. It is worth noting that the cross-lagged effects (noted as γ parameters in Figure 1) estimated in the cross-lagged model are inherently the same as the coupling effects (also noted as γ parameters or level-to-change effects in Figure 7) estimated in the latent change score model. For example, in our analyses, the cross-lagged effects of X on Y in Model 1a represent the influences of X at Time t on Y at Time t+1 controlling for the self-influence of Y at Time t (e.g. Liu et al., 2015), which is conceptually the same as the coupling effects of x at Time t on Δy at Time t+1 in Model 3a. Unlike the cross-lagged model, one unique aspect of the latent change score model is that it also estimates a different form of causality: the change-to-change effects over time (i.e. ζ parameters in Figure 7). Although the simulated data used in the current article show that both γ_{yx} (.11, $p < .01$) and ζ_{yx} (.33, $p < .01$) were significant and positive, these two parameters actually have different meanings in terms of causal inference and therefore can deviate from each other (e.g. Taylor et al., in press): significant γ_{yx} parameters indicate an *absolute* feature of the X–Y relationship such that the absolute level of X predicts the changes in Y, while significant ζ_{yx} parameters indicate a *relative* feature of the X–Y relationship such that it is the deviance of X from X's prior value that predicts the changes in Y.

The latent growth model, on the other hand, usually offers little insight on causal inference. This is because most of studies using the cross-domained latent growth models specified latent growth models across the same span of measurement window (Selig & Preacher, 2009). If this is the case, the estimated associations among the latent growth curves only represent covarying relationships rather than causal relationships. For example, in our analysis of Model 2d, although both the covariance between Slope_X and Slope_Y ($\varphi = .07$, $p < .01$) and the covariance between $\text{Quadratics}_\text{X}$ and Slope_Y ($\varphi = -.01$, $p < .01$) were significant, it does not indicate a causal relationship between the changes in X and Y over time because the survey window of X and Y completely overlapped. To enhance causal inference, it may be preferable to use a sequential process latent growth model, in which X would be measured repeatedly on some interval t_0 to t_j and Y would be measured repeatedly on some interval t_j to t_i (Selig & Preacher, 2009). This recommendation is consistent with studies that used time-invariant variables to predict the slope factor (Christie & Barling, 2009) or different change patterns of the growth curve (e.g. Wang, 2007) in latent growth models; essentially, these practices also generate estimates for potential level-to-change effects.

In sum, both the cross-lagged model and the latent change score model can enhance the causal inference of the relationships studied between different variables by revealing the associations between different variables over time. Moreover, the latent change score model can provide one more piece of information regarding the form of causality among the studied variables, i.e. the associations between *changes* among different variables over time. The latent growth model is limited in offering information on causal inference.

Change Description

Besides inferring causality, another major focus of longitudinal analysis is to describe changes in constructs (McArdle, 2009). In fact, most organisational theories more or less involve theories of change. As such, using longitudinal analysis to describe changes will help researchers to advance their understanding of the changing nature of their theories, including the duration and timing of the change, the form of the change, and the potential causes of the change (Ployhart & Vandenberg, 2010). In fact, Kelloway and Francis (2013) pointed out that very few OHP studies aim to describe changes in OHP phenomena and they suggested that OHP researchers could actually learn a lot from a descriptive understanding of longitudinal data, such as the temporal progression of workplace stressors and the chronic development of employee strain.

In our demonstration, the latent growth model and the latent change score model are both able to reveal the changing trend in constructs over time. On the one hand, the latent growth model allows us to specify different forms of change (e.g. linear change or quadratic change) and to select the change trajectory that best describes the longitudinal data, as depicted in Figure 5. On the other hand, the latent change score model provides a comprehensive estimation of changes in different forms (e.g. α and β parameters) and other sources of influence leading to changes in a particular construct (e.g. γ and ζ parameters). These pieces of information together can be combined to depict the predicted changing trajectory of each construct over time, as depicted in Figure 8.

Although latent slope factors are specified in both the latent growth model and the latent change score model, they have different meanings in the two models. For example, in the latent growth model shown in Figure 2, the slope factor represents the average rate of linear change in the measured variables over time. If the non-linear rate of change is sought, one has to change the factor loading structures on the latent slope factor or include additional latent factors to capture the non-linear changing trend (as we did in the analysis of Model 2d). In the latent change score model, however, the slope factor represents the average rate of change in the latent change scores over time. As a convention, the factor loadings of the slope factor (i.e. α parameters) on the latent change variable in the latent change score model are usually fixed at 1.0. Therefore, the slope factor actually represents the constant change in the latent change score over time, the magnitude of which is determined by the mean value of the latent slope factor (i.e. θ_X in Figure 3 and θ_{sx} and θ_{sy} in Figure 7). For the univariate latent change score model, this constant change along with the proportional change represented by β parameters will determine the changing trajectory of the construct. For the multivariate latent change score model, this constant change along with the proportional change, the level-to-change effects (i.e. γ parameters), and the change-to-change effects (i.e. ζ parameters) will determine the changing trajectory of each construct. Unlike the latent growth model, there is no need to specify any additional latent factors to represent non-linear changes because the effects of α and β parameters will be both accumulated over time and are able to reveal a non-linear changing trend.

Interestingly, a comparison between Figure 5 and Figure 8 shows that the predicted changing trajectories derived from the latent growth model and the latent change score model are very similar. Note that the trajectories depicted in Figure 5 were based on the best-fitting latent growth models selected from a group of possible models, while the trajectories depicted in Figure 8 were based solely on the parameters estimated in the bivariate latent change score model (i.e. Model 3a). This suggests that it is possible to use the bivariate latent change score model to obtain parameter estimations with desirable fit even when the best-fitting changing trajectory of each construct is not estimated a priori.

In sum, both the latent growth model and the latent change score model are useful in describing changes (especially the form of changes) in one or more constructs over time. Moreover, the latent change score model has the advantage of isolating different forms of change and being more convenient in revealing the predicted changing trajectory. The cross-lagged model offers little information on the overall changing trend in constructs over time.

Issues of Modeling and Interpretation

As we present in the Appendix, the basic cross-lagged model between two variables is easy to specify. However, several issues are important to note if one wants to make extensions to this basic model. First, when the constructs are measured with multiple indicators, it is preferable to model the cross-lagged effects and the autoregressive effects using latent constructs to alleviate concerns of measurement errors. Second, when more than two constructs are modeled using the cross-lagged model, mediation tests of possible indirect effects are necessary to consider (Selig & Preacher, 2009). For example, indirect effects representing different causal orders can be tested and compared. Third, when modeling the cross-lagged model using data with more than three time occasions, we suggest testing lagged and autoregressive effects across more than one time lag (e.g. testing second-order lagged/autoregressive effects) as a robust check of the hypothesised effects (e.g. Meier & Spector, 2013). Fourth, if equality constraints are imposed on the parameters to be estimated, it is important to conduct model comparison tests to obtain evidence of imposing such constraints. Fifth, the cross-lagged model requires equal time intervals between any two adjacent measurement points, especially when equality constraints on parameters are desired.

Modeling and interpreting the associations among changes in multiple constructs using the latent growth model also requires some caution. First, it is important to use the univariate latent growth model in the first place to determine the best-fitting model for each growth curve, the estimated parameters (e.g. factor loadings, means, and variances of the latent intercept and slope) which are needed to build the cross-domain latent growth model. Second, when more than two constructs are modeled using the latent growth model, it is necessary to consider mediation tests of possible indirect effects (Selig & Preacher, 2009). Third, one needs to be careful in interpreting the associations between slope factors among different constructs, which may not be able to offer causal inference if there is no time separation between the two constructs. Fourth, if the univariate latent growth curve involves additional factors (e.g. a quadratics factor) besides the intercept and slope factor, the associations among these additional factors and latent factors of other constructs may be difficult to interpret, such as the negative covariance ($r = -.01$, $p < .01$) between the quadratics factor of X and the slope factor of Y presented in Figure 6. Fifth, unlike in the cross-lagged model, it is not necessary for the latent growth model to have equal time intervals on its measures. Instead, the latent growth model can cater to different measurement time intervals by rescaling the factor loadings of the slope factor to match the different time intervals. For instance, if the time interval is one month between Time 1 and Time 2 and between Time 2 and Time 3, while the time interval is two months between Time 3 and Time 4 and between Time 4 and Time 5, one can still fit a linear latent growth model by using [1.0, 2.0, 3.0, 5.0, 7.0] as the factor loadings of the repeated measures on the slope factor. However, we still recommend that researchers collect longitudinal data with equal time intervals between measurement points if the situation allows, which will grant them more freedom in choosing between different techniques of longitudinal analysis.

Finally, some suggestions regarding modeling and interpreting the latent change score include: First, due to the modeling complexity, it is quite possible that one cannot get a converging model. In this case, imposing constraints on parameters (e.g. equality constraints) may help the model to converge, but careful examination of model fit is necessary to justify each of the imposed constraints on parameters. Second, when more than two constructs are modeled using the latent change score model, mediation tests of possible indirect effects are necessary to consider, such as the eight possible indirect effects among the levels and changes for the case of three constructs (Selig & Preacher, 2009). Third, while the interpretation of parameters across constructs (e.g. γ and ζ parameters) is relatively straightforward, the interpretation of parameters describing self-change (e.g. α and β parameters) is less obvious. We suggest that researchers plot out the changing trajectory of each construct with information estimated from the model. For example, in Figure 8, the predicted value of x1 is the estimated mean of the latent intercept factor of x (θ_{ix}); the predicted value of x2 is the sum of the predicted value of x1 and the predicted value of Δx2, which is a function of x1 and y1 (i.e. $\Delta x2 = \alpha_x{*}\theta_{ix} + \beta_x{*}x1 + \gamma_{xy}{*}y1$); the predicted value of x3 is the sum of the predicted value of x2 and the predicted value of Δx3, which is a function of x2, y2, and Δy2 (i.e. $\Delta x3 = \alpha_x{*}\theta_{ix} + \beta_x{*}x2 + \gamma_{xy}{*}y2 + \zeta_{xy}{*}\Delta y2$), and so on. Fourth, similar to the cross-lagged model, the latent change score model is most consistently specified with equal time intervals on its measures, because it assumes that latent variables are equidistant in time even if the observed variables are not (McArdle, 2009). Therefore, an equal time interval between the observed variables makes it possible to fix the constant change loadings of the latent slope factor on the latent variables (i.e. α parameters) to be at 1.0

Conclusion

As a final summary of this article, we offer a brief recommendation on which of the three techniques is preferable depending on the particular research question. Specifically, if the research question is to examine the causal relationships among multiple variables over time, both the cross-lagged model and the latent change score model can be used. If the research question is to describe the changes in one or more variables over time, both the latent growth model and the latent change score model can be used. If the research question is to both describe the changes and to detect the causal relationships among multiple variables over time, only the latent change score model can be used to address such a research question. We hope this review and tutorial can be useful for facilitating the implementation of longitudinal design and analyses in the field of OHP.

REFERENCES

Bentein, K., Vandenberghe, C., Vandenberg, R., & Stinglhamber, F. (2005). The role of change in the relationship between commitment and turnover: A latent growth modeling approach. *Journal of Applied Psychology*, *90*, 468–482.

Bollen, K.A., & Curran, P.J. (2004). Autoregressive latent trajectory (ALT) models a synthesis of two traditions. *Sociological Methods & Research*, *32*, 336–383.

Burkholder, G.J., & Harlow, L.L. (2003). An illustration of a longitudinal cross-lagged design for larger structural equation models. *Structural Equation Modeling*, *10*, 465–486.

Chan, D. (1998). The conceptualization and analysis of change over time: An integrative approach incorporating longitudinal mean and covariance structures analysis (LMACS) and multiple indicator latent growth modeling (MLGM). *Organizational Research Methods*, *1*, 421–483.

Chan, D. (2011). Advances in analytical strategies. In S. Zedeck (Ed.), *APA handbook of industrial and organizational psychology: Vol. 1. Building and developing the organization* (pp. 85–113). Washington, DC: American Psychological Association.

Christie, A.M., & Barling, J. (2009). Disentangling the indirect links between socioeconomic status and health: The dynamic roles of work stressors and personal control. *Journal of Applied Psychology*, *94*, 1466–1478.

Curran, P.J., & Bollen, K.A. (2001). The best of both worlds: Combining autoregressive and latent curve models. In L.M. Collins & A.G. Sayer (Eds.), *New methods for the analysis of change* (pp. 105–136). Washington, DC: American Psychological Association.

Demerouti, E., Bakker, A.B., & Bulters, A.J. (2004). The loss spiral of work pressure, work–home interference and exhaustion: Reciprocal relations in a three-wave study. *Journal of Vocational Behavior*, *64*, 131–149.

DeShon, R.P. (2012). Multivariate dynamics in organizational science. In S.W.J. Kozlowski (Ed.), *The Oxford handbook of organizational psychology* (pp. 117–142). New York: Oxford University Press.

Ferrer, E., & McArdle, J.J. (2003). Alternative structural models for multivariate longitudinal data analysis. *Structural Equation Modeling*, *10*, 493–524.

Ferrer, E., & McArdle, J.J. (2010). Longitudinal modeling of developmental changes in psychological research. *Current Directions in Psychological Science*, *19*, 149–154.

Fuller, J.A., Stanton, J.M., Fisher, G.G., Spitzmüller, C., Russell, S.S., & Smith, P.C. (2003). A lengthy look at the daily grind: Time series analysis of events, mood, stress, and satisfaction. *Journal of Applied Psychology*, *88*, 1019–1033.

Gabriel, A., & Diefendorff, J. (in press). Emotional labor dynamics: A momentary approach. *Academy of Management Journal.* doi:10.5465/amj.2013.1135

Garst, H., Frese, M., & Molenaar, P. (2000). The temporal factor of change in stressor–strain relationships: A growth curve model on a longitudinal study in East Germany. *Journal of Applied Psychology*, *85*, 417–438.

Grimm, K.J. (2007). Multivariate longitudinal methods for studying developmental relationships between depression and academic achievement. *International Journal of Behavioral Development*, *31*, 328–339.

Halbesleben, J.R. (2010). The role of exhaustion and workarounds in predicting occupational injuries: A cross-lagged panel study of health care professionals. *Journal of Occupational Health Psychology*, *15*, 1–16.

Halbesleben, J.R.B., & Wheeler, A.R. (2015). To invest or not? The role of coworker support and trust in daily reciprocal gain spirals of helping behavior. *Journal of Management*, *41*, 1628–1650.

Hsiao, C. (2003). *Analysis of panel data* (2nd edn.). London: Cambridge University Press.

Hülsheger, U.R., Lang, J.W., & Maier, G.W. (2010). Emotional labor, strain, and performance: Testing reciprocal relationships in a longitudinal panel study. *Journal of Occupational Health Psychology*, *15*, 505–521.

James, L.R., Mulaik, S.A., & Brett, J.M. (1982). *Causal analysis: Assumptions, models, and data* (Vol. 1). Beverly Hills, CA: Sage Publications.

Jones, K.P., King, E.B., Gilrane, V.L., McCausland, T.C., Cortina, J.M., & Grimm, K.J. (in press). The baby bump: Managing a dynamic stigma over time. *Journal of Management.* doi:10.1177/0149206313503012

Judge, T.A., Simon, L.S., Hurst, C., & Kelley, K. (2014). What I experienced yesterday is who I am today: Relationship of work motivations and behaviors to within-individual variation in the five-factor model of personality. *Journal of Applied Psychology*, *99*, 199–221.

Kammeyer-Mueller, J.D., Wanberg, C.R., Rubenstein, A.L., & Song, Z. (2013). Support, undermining, and newcomer socialization: Fitting in during the first 90 days. *Academy of Management Journal*, *56*, 1104–1124.

Kelloway, E.K., & Francis, L. (2013). Longitudinal research and data analysis. In R.R. Sinclair, M. Wang, & L.E. Tetrick (Eds.), *Research methods in occupational health psychology: Measurement, design and data analysis* (pp. 374–394). New York: Routledge.

Lang, J., Bliese, P.D., Lang, J.W., & Adler, A.B. (2011). Work gets unfair for the depressed: Cross-lagged relations between organizational justice perceptions and depressive symptoms. *Journal of Applied Psychology*, *96*, 602–618.

Li, W.D., Fay, D., Frese, M., Harms, P.D., & Gao, X.Y. (2014). Reciprocal relationship between proactive personality and work characteristics: A latent change score approach. *Journal of Applied Psychology*, *99*, 948–965.

Liu, S., Wang, M., Zhan, Y., & Shi, J. (2009). Daily work stress and alcohol use: Testing the cross-level moderation effects of neuroticism and job involvement. *Personnel Psychology*, *62*, 575–597.

Liu, Y., Wang, M., Chang, C.H., Shi, J., Zhou, L., & Shao, R. (2015). Work–family conflict, emotional exhaustion, and displaced aggression toward others: The moderating roles of workplace interpersonal conflict and perceived managerial family support. *Journal of Applied Psychology*, *100*, 793–808.

McArdle, J.J. (2001). A latent difference score approach to longitudinal dynamic structural analyses. In R. Cudeck, S. du Toit, & D. Sorbom (Eds.), *Structural equation modeling: Present and future* (pp. 342–380). Lincolnwood, IL: Scientific Software International.

McArdle, J.J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology*, *60*, 577–605.

Maxwell, S.E., & Cole, D.A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods*, *12*, 23–44.

Meier, L.L., & Spector, P.E. (2013). Reciprocal effects of work stressors and counterproductive work behavior: A five-wave longitudinal study. *Journal of Applied Psychology*, *98*, 529–539.

Muthén, L.K., & Muthén, B.O. (1998–2012). *Mplus user's guide* (7th edn.). Los Angeles, CA: Muthén & Muthén.

Ployhart, R.E., & Vandenberg, R.J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management*, *36*, 94–120.

Rodríguez-Muñoz, A., Baillien, E., De Witte, H., Moreno-Jiménez, B., & Pastor, J.C. (2009). Cross-lagged relationships between workplace bullying, job satisfaction and engagement: Two longitudinal studies. *Work & Stress*, *23*, 225–243.

Rovine, M.J., & Molenaar, P.C. (2005). Relating factor models for longitudinal data to quasi-simplex and NARMA models. *Multivariate Behavioral Research*, *40*, 83–114.

Selig, J.P., & Preacher, K.J. (2009). Mediation models for longitudinal data in developmental research. *Research in Human Development*, *6*, 144–164.

Smith, L.G., Amiot, C.E., Smith, J.R., Callan, V.J., & Terry, D.J. (2013). The social validation and coping model of organizational identity development: A longitudinal test. *Journal of Management*, *39*, 1952–1978.

Taris, T. (2003). Challenges in longitudinal designs in OHP. *Scandinavian Journal of Work and Environmental Health*, *29*, 1–4.

Taylor, S.G., Bedeian, A.G., Cole, M.S., & Zhang, Z. (in press). Developing and testing a dynamic model of workplace incivility change. *Journal of Management*. doi:10.1177/0149206314535432

Tetrick, L.E., & Quick, J.C. (2011). Overview of occupational health psychology: Public health in occupational settings. In L.E. Tetrick & J.C. Quick (Eds.), *Handbook of occupational health psychology* (pp. 3–20). Washington, DC: American Psychological Association.

Toker, S., & Biron, M. (2012). Job burnout and depression: Unraveling their temporal relationship and considering the role of physical activity. *Journal of Applied Psychology*, *97*, 699–710.

Vancouver, J.B., & Weinhardt, J.M. (2012). Modeling the mind and the milieu computational modeling for micro-level organizational researchers. *Organizational Research Methods*, *15*, 602–623.

Vandenberghe, C., Panaccio, A., Bentein, K., Mignonac, K., & Roussel, P. (2011). Assessing longitudinal change of and dynamic relationships among role stressors, job attitudes, turnover intention, and well-being in neophyte newcomers. *Journal of Organizational Behavior*, *32*, 652–671.

Wang, J., & Wang, X. (2012). *Structural equation modeling: Applications using Mplus*. Chichester: John Wiley & Sons.

Wang, M. (2007). Profiling retirees in the retirement transition and adjustment process: Examining the longitudinal change patterns of retirees' psychological well-being. *Journal of Applied Psychology*, *92*, 455–474.

Wang, M., & Bodner, T.E. (2007). Growth mixture modeling: Identifying and predicting unobserved subpopulations with longitudinal data. *Organizational Research Methods*, *10*, 635–656.

Wang, M., & Chan, D. (2011). Mixture latent Markov modeling: Identifying and predicting unobserved heterogeneity in longitudinal qualitative status change. *Organizational Research Methods*, *14*, 411–431.
Wang, M., & Hanges, P. (2011). Latent class procedures: Applications to organizational research. *Organizational Research Methods*, *14*, 24–31.
Wang, M., Liu, S., Liao, H., Gong, Y., Kammeyer-Mueller, J., & Shi, J. (2013). Can't get it out of my mind: Employee rumination after customer mistreatment and negative mood in the next morning. *Journal of Applied Psychology*, *98*, 989–1104.
Wang, M., Liu, S., Zhan, Y., & Shi, J. (2010). Daily work–family conflict and alcohol use: Testing the cross-level moderation effects of peer drinking norms and social support. *Journal of Applied Psychology*, *95*, 377–386.
Zapf, D., Dormann, C., & Frese, M. (1996). Longitudinal studies in organizational stress research: A review of the literature with reference to methodological issues. *Journal of Occupational Health Psychology*, *1*, 145–169.
Zyphur, M.J., Chaturvedi, S., & Arvey, R.D. (2008). Job performance over time is a function of latent trajectories and previous performance. *Journal of Applied Psychology*, *93*, 217–224.

APPENDIX: SELECTED Mplus SYNTAX

Model 1a: Unconstrained Cross-Lagged Model

```
MODEL:
    ! specifying autoregression effects
    x2 on x1; x3 on x2; x4 on x3; x5 on x4; x6 on x5;
    y2 on y1; y3 on y2; y4 on y3; y5 on y4; y6 on y5;

    ! specifying cross-lagged effects
    x2 on y1; x3 on y2; x4 on y3; x5 on y4; x6 on y5;
    y2 on x1; y3 on x2; y4 on x3; y5 on x4; y6 on x5;

    ! specifying covariance between x and y
    x1 with y1; x2 with y2; x3 with y3; x4 with y4; x5 with y5; x6 with y6;
```

Model 2d: Bivariate Latent Growth Model

```
MODEL:
    ! specifying latent intercept and slope factors
    ix by x1@1 x2@1 x3@1 x4@1 x5@1 x6@1;
    sx by x1@0 x2@1 x3@2 x4@3 x5@4 x6@5;
    qx by x1@0 x2@1 x3@4 x4@9 x5@16 x6@25;
    iy by y1@1 y2@1 y3@1 y4@1 y5@1 y6@1;
    sy by y1@0 y2@1 y3@2.26y4@3.22y5@4.21y6@5.14;

    ! specifying mean and variance structures
    [x1-x6@0];
    [y1-y6@0];
    [ix@.801 sx@.350 qx@-.024 iy@.337 sy@.571];
```

(Continued)

```
! specifying covariances among latent factors
ix with sx qx;
sx with qx;
iy with sy;
ix with iy sy;
sx with iy sy;
qx with iy sy;
```

Model 3a: Bivariate Latent Change Score Model

```
MODEL:
    ! x variable
    ! specifying latent variables and the autoregressive effects among latent variables
    lx1 by x1@1; lx2 by x2@1; lx3 by x3@1; lx4 by x4@1; lx5 by x5@1; lx6 by x6@1;
    lx2 on lx1@1; lx3 on lx2@1; lx4 on lx3@1; lx5 on lx4@1; lx6 on lx5@1;

    ! specifying latent change score variables measured by latent variables
    dx2 by lx2@1; dx3 by lx3@1; dx4 by lx4@1; dx5 by lx5@1; dx6 by lx6@1;

    ! specifying beta paths
    dx2 on lx1 (1); dx3 on lx2 (1); dx4 on lx3 (1); dx5 on lx4 (1); dx6 on lx5 (1);

    ! specifying latent intercept and slope factors
    ix by lx1@1;
    sx by dx2@1; sx by dx3@1; sx by dx4@1; sx by dx5@1; sx by dx6@1;
    sx with ix; [sx ix]; sx; ix;

    ! specifying mean and variance structures
    [x1-x6@0];[lx1-lx6@0];[dx2-dx6@0];lx1-lx6@0;dx2-dx6@0;
    x1-x6 (2);

    ! y variable
    ! specifying latent variables and the autoregressive effects among latent variables
    ly1 by y1@1; ly2 by y2@1; ly3 by y3@1; ly4 by y4@1; ly5 by y5@1; ly6 by y6@1;
    ly2 on ly1@1; ly3 on ly2@1; ly4 on ly3@1; ly5 on ly4@1; ly6 on ly5@1;

    ! specifying latent change score variables measured by latent variables
    dy2 by ly2@1; dy3 by ly3@1; dy4 by ly4@1; dy5 by ly5@1; dy6 by ly6@1;

    ! specifying beta paths
    dy2 on ly1 (3); dy3 on ly2 (3); dy4 on ly3 (3); dy5 on ly4 (3); dy6 on ly5 (3);

    ! specifying latent intercept and slope factors
    iy by ly1@1;
    sy by dy2@1; sy by dy3@1; sy by dy4@1; sy by dy5@1; sy by dy6@1; sy with iy;
    [sy iy]; sy; iy;

    ! specifying mean and variance structures
    [y1-y6@0];[ly1-ly6@0];[dy2-dy2@0];ly1-ly6@0;dy2-dy2@0;
    y1-y6 (4);
```

(Continued)

```
! specifying gamma and zeta paths
dy2 on lx1 (5);
dy3 on lx2 (5)
   dx2 (6);
dy4 on lx3 (5)
   dx3 (6);
dy5 on lx4 (5)
   dx4 (6);
dy6 on lx5 (5)
   dx5 (6);
dx2 on ly1 (7);
dx3 on ly2 (7)
   dy2 (8);
dx4 on ly3 (7)
   dy3 (8);
dx5 on ly4 (7)
   dy4 (8);
dx6 on ly5 (7)
   dy5 (8);
```