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Dynamic Modeling

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Abstract

Recent effort in organizational psychology and organizational behavior (OPOB) research has placed increasing emphasis on understanding dynamic phenomena and processes. This calls for more and better use of dynamic modeling in OPOB research than before. The goals of this review are to provide an overview of the general forms of dynamic modeling in OPOB research, discuss three longitudinal data analytic techniques for conducting dynamic modeling with empirical data [i.e., time-series-based modeling, latent-change-scores-based modeling, and functional data analysis (FDA)], and introduce various dynamic modeling approaches for building theories about dynamic phenomena and processes (i.e., agent-based modeling, system dynamics modeling, and hybrid modeling). This review also highlights several OPOB research areas to which dynamic modeling has been applied and discusses future research directions for better utilizing dynamic modeling in those areas.

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INTRODUCTION

Recent effort in organizational psychology and organizational behavior (OPOB) research has placed increasing emphasis on understanding dynamic phenomena and processes that are critical for worker well-being and productivity. These include self-regulation processes (e.g., Vancouver et al. 2014), workplace emotions and emotional labor (e.g., Beal et al. 2013, Gabriel & Diefendorff 2015), workplace stress and well-being (e.g., Fuller et al. 2003, Sonnentag 2015, Wang et al. 2013), job search (e.g., Liu et al. 2014, Wanberg et al. 2012), and newcomer adjustment (e.g., Kammeyer-Mueller et al. 2013), just to name a few. In addition, the study of dynamic phenomena and processes has also made important progress in team science, especially in terms of understanding the development of team emergent states (e.g., Dionne et al. 2010, Kozlowski & Chao 2012). In fact, in a content analysis of the 193 articles published in the first 10 volumes of *Organizational Research Methods*, Aguinis et al. (2009) showed that temporal issues is one of the most popular quantitative topics covered by the journal.

Although dynamic modeling has much to contribute to this increasing research focus, a systematic review on dynamic modeling for the purposes of longitudinal data analysis and dynamic theory building is still missing for OPOB research [see DeShon's (2012) overview on the analysis of stationary dynamic systems for an exception]. Therefore, the current article seeks to fill this gap by providing an overview of the general forms of dynamic modeling in OPOB research, data analytic techniques for using dynamic modeling to analyze empirical data, and various dynamic modeling approaches for building theories about dynamic phenomena and processes. We also highlight several OPOB research areas to which dynamic modeling has been applied and discuss future research directions for better utilizing dynamic modeling in those areas. Our purpose with this overview is to better expose the OPOB researchers to the general utilities, principles, and approaches of dynamic modeling and illustrate ways to further use dynamic modeling to advance knowledge and theories in this field. To enhance accessibility, for all the dynamic modeling techniques and approaches reviewed in this article, we summarize their key features, matching research questions, exemplar studies, strengths, weaknesses, and relevant practical and logistical issues in **Table 1**.

GENERAL FORMS OF DYNAMIC MODELING IN ORGANIZATIONAL PSYCHOLOGY AND ORGANIZATIONAL BEHAVIOR RESEARCH

A dynamic model can be defined as a representation of a system that evolves over time (Galor 2007, Luenberger 1979). In particular, it describes how the system evolves from a given state at time t to another state at time $t + 1$, as governed by the transition rules and potential external inputs. In OPOB research, a system represented by a dynamic model can contain as few as one dynamic variable whose values fluctuate over time [see, e.g., Edwards (1992) on work stress]. Alternatively, a dynamic model can contain multiple dynamic variables that change over time [see, e.g., Kozlowski & Chao (2012) on team emergent states]. Whether representing a simple or complex system, the components in a dynamic model are governed by transition rules that specify how the system moves from one state to another. When the system only contains one dynamic variable, the transition rules have to specify how the earlier state of the variable determines the later state of the same variable. When the system contains more than one dynamic variable, the transition rules may also specify the interrelations among the dynamic variables. As such, the states of dynamic variables may be functions of their own previous states (e.g., $X_t \rightarrow X_{t+1}$, $Y_t \rightarrow Y_{t+1}$) and/or the states of other dynamic variables in the system (e.g., $Y_t \rightarrow X_{t+1}$, $X_t \rightarrow Y_{t+1}$). Although external inputs (e.g., unexpected shocks from the external environment) may alter the course of the observed dynamic trend of the system state, a dynamic model does not have to contain external

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Table 1 Summary of dynamic modeling techniques and approaches

	Key features	Research questions that are best addressed and exemplar studies	Strengths	Weaknesses	Practical and logistical issues
Time-series-based modeling	Explicitly considers temporal structure in data in terms of autocorrelation, trends, and seasonal effects; can be parametric (for testing a stochastic model) or nonparametric (for forecasting future values); focuses on within-subject relationships; small N and large T	How do the intraindividual relationships among repeatedly measured x, m, and y unfold over time for a single subject or a few subjects (Fuller et al. 2003)?	Stronger causal inferences as a result of focusing on intraindividual relationships	A potential lack of generalizability to other subjects; analytically complex multisubject time-series modeling	Requires intensive longitudinal data
Latent-change-scores-based modeling	Defines change of a variable from t to $t+1$ as a latent variable; change consists of a constant change and a change that is proportional to the prior status of the same variable; latent change variable can serve as a predictor, mediator, outcome, and/or moderator; large N and small T	Does the level of variable x at time t predict the change in variable y (from t to $t+1$)? Does the change in x (from t to $t+1$) predict a subsequent change in y (from $t+1$ to $t+2$)? Is there a mediation effect involving one or more latent change variables (Taylor et al. 2014)?	Able to model nonlinear trajectories that are not accommodated in latent growth curve models; latent change variable can be embedded in a complex model of relationships	Generalizability to a wider time window is a potential concern given coverage of only a limited number of time periods; equal constraints on paths across points are often needed, but could be unrealistic	Model specified often complex, resulting in issues with model identification and estimation; necessity of large sample size at the between-subject level to warrant sufficient model identification
Functional data analysis	Based on very densely measured variables; data point is a curve (e.g., variable x plotted over time); researchers use functions (e.g., velocity and acceleration) of curves as predictors, mediators, or outcome variables; large/moderate N and large T	How is a single curve shaped, and when does a certain event occur on this curve? What are the relationships between variable x curve's velocity and variable y curve's acceleration across time (Hu et al. 2014)?	Both between-subject and within-subject relationships examined; able to examine when an event occurred and how fast the subject responded to it	Limited to variables that can be (almost) continuously measured, e.g., blood pressure or mood	Needs to have high sampling rate to maintain high resolution of the curve; data collection may require extensive resources

(*Continued*)

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Table 1 (*Continued*)

	Key features	Research questions that are best addressed and exemplar studies	Strengths	Weaknesses	Practical and logistical issues
Agent-based modeling	Defines the interaction rules among multiple agents (e.g., individuals) in the same system (e.g., team); uses "agents," who have attributes and self-contained rules, to represent multiple actors in social interactions in a given environment	What is the pattern of interactions among multiple agents in the same system? How, how fast, and when do collective team states (e.g., cohesion) emerge from interactions among agents (Guimerà et al. 2005)?	Can easily incorporate number of agents as a parameter in the model to examine the effect of system size; examines microprocesses and macroproperties simultaneously	Role of time often assumed to be discrete, as the interaction unfolds step by step rather than "truly" continuously	Requires researchers' basic understanding of computer programming and reporting of the technical details of simulating the models, which can be challenging; the necessity of numerous observations for empirical tests of the specified processes
System dynamics modeling	Concerned about maintenance or regulation toward a specific state within the same system (e.g., one individual); includes one or more state variables, a series of causal loops, often negative feedback loops, and sometimes positive feedback loops	How long does it take for a system to recover to its normal state after a shock from the external environment? How long does it take for a system to regulate toward the ideal state? How does the state (e.g., stress) of a system (e.g., an individual) and a particular action (e.g., coping) of the system influence each other over time (Vancouver et al. 2010a,b)?	Specification of time possible as continuous or discrete; same negative feedback loop structure can be used as building blocks to account for complex regulatory systems	Incorporating complex interactions among several agents can be cumbersome; does not always concern emergence from lower-level actors to higher-level units	
Hybrid modeling	Includes dynamic processes that represent multiple theoretical mechanisms	How do three interrelated processes drive the observed relationship between variable *X* and variable *Y* (Carroll & Harrison 1998)?	Flexibly integrates multiple forms of dynamic processes	The model could be very complex, which can make model simulation and evaluation difficult	

inputs to sustain change in the state over time. In other words, a dynamic model can be constructed with simply the initial state of the system and the governing transition rules (DeShon 2012).

In OPOB research, our research questions regarding dynamic phenomena and processes often point to the need for understanding how values of variables change over time and the causes of those value changes. Both of these research goals can be addressed by examining the transition rules that govern the dynamic system in question. However, most of time, these transition rules are not immediately observable, hence the need for conducting dynamic modeling. In OPOB research, depending on the research goal, dynamic modeling typically takes one of two general forms, which serve different utilities. First, dynamic modeling often takes the form of longitudinal data analysis when data regarding the dynamic system's state over time exist. In this case, researchers may conduct dynamic modeling by using longitudinal data analytic techniques to estimate or recover the underlying transition rules that govern the dynamic states of the system. For example, Taylor et al. (2014) tested a dynamic model on workers' turnover cognition. They gathered data from 131 employees on a weekly basis for six consecutive weeks on three variables: workplace incivility, job burnout, and turnover cognition. The repeated measures of these variables are construed as observations of a dynamic system for six weeks (considering time as a discrete variable). Using these longitudinal data and applying the latent-change-score (LCS) model, these authors tested a dynamic model where one of the underlying transition rules specified that the change in workplace incivility was related to the subsequent change in job burnout which, in turn, related to change in turnover cognition. By estimating coefficients that link LCSs in this dynamic model, Taylor et al. (2014) found support for this transition rule (i.e., a significant mediation effect from change in workplace incivility to change in turnover cognition via change in job burnout). Although the mediation effect was central to addressing the research question in this case, other underlying transition rules were also incorporated in the estimated model (e.g., for each variable, subsequent change was also specified to be proportional to the variable's previous state) to achieve good model-data fit. Therefore, dynamic modeling in the form of longitudinal data analysis needs to sufficiently model the possibility that states of dynamic variables may be functions of both their own previous states and the states of other dynamic variables in the model.

A second form that dynamic modeling takes in OPOB research is as a theory-building tool that generates theories explaining dynamic phenomena and processes. This is often done when the interested phenomena or processes are complex and/or relatively few empirical data exist. In this case, verbal language may not be able to capture the complex underlying transition rules that drive the dynamic phenomena or processes. Furthermore, it is difficult to estimate the dynamic model as a statistical model with limited data to accurately uncover the transition rules. When this is the case, dynamic modeling can be carried out using computational modeling approaches, which refer to the processes of building theories that represent the dynamics of interest using computational languages and evaluating various potential transition rules on the basis of the computational models specified. In particular, a computational model can be constructed to represent the likely transition rules underlying dynamic phenomena and processes using formal logics (e.g., "if X, then Y") and equations (e.g., "$X = k^{*}Y/Z$"; Taber & Timpone 1996). As such, by specifying the potential transition rules into computational forms, the components of a dynamic model and their relations are mathematically defined. More importantly, the theoretical role of time is explicitly represented in this type of dynamic modeling, often through defining a process sequence or the rate of change (Davis et al. 2007, Harrison et al. 2007). The resulting computational model thus offers a formal theory about the focal dynamic phenomena and processes that can be simulated and evaluated.

Researchers can evaluate several aspects of the formal theory resulting from dynamic modeling, including (*a*) whether the simulated outputs of the computational model are coherent, (*b*) how well

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the computational model's prediction fits the real-world data, (*c*) whether the model-data fit of the proposed model (i.e., the focal transition rules) outperforms the alternative models (i.e., other potential transition rules), and (*d*) the extent to which the computational model's prediction holds in sensitivity analysis or robustness checks (Taber & Timpone 1996). Empirically testing dynamic computational models involves collecting longitudinal data using empirical research methods (e.g., laboratory and field experiments, archival data analyses, field studies, etc.). Therefore, simulation is just one approach to assess the quality of the proposed theoretical model. When sufficient empirical data are available, the dynamic modeling returns to the form of longitudinal data analysis and the empirical modeling results can be used to further extend or modify the transition rules represented in the computational models. In this sense, the two forms of dynamic modeling in OPOB research together represent an iterative process that combines theory testing and theory development, which is necessary to reach a deeper understanding about complex dynamic phenomena and processes.

Before moving to the next section, we also highlight the strengths for using dynamic modeling as a theory-building tool in OPOB research and call for more research to take this approach for theory development. First, compared to verbal language theories (i.e., the most commonly used theorizing approach in OPOB research), computational models of dynamics are more precise about the assumptions, boundary conditions, and mechanisms studied, especially regarding the theoretical role of time (Davis et al. 2007, Harrison et al. 2007). Due to its clarity, using dynamic modeling for theory building is especially powerful for scrutinizing assumptions of existing theories, refining theoretical arguments, maintaining consistency in the logic, and comparing or integrating mechanisms and processes proposed by prior research. In addition, computational models of dynamics are more flexible for specifying some concepts that are difficult to define clearly in verbal language (e.g., connectionist models; Lord et al. 2001).

Second, as compared to deduction-based theory development, dynamic modeling is particularly suitable for studying complicated organizational phenomena that involve multiple interdependent dynamic processes across multiple levels (Davis et al. 2007, Harrison et al. 2007). Theoretical relations specified in deductive forms can sometimes be intractable (i.e., cannot be solved mathematically) for complex processes (Harrison et al. 2007). However, dynamic modeling in the form of computational modeling directly addresses this issue by deriving predictions from the formal theory through computationally carrying out the transition rules and generating the system outputs over time at the given initial state of the system (i.e., input values). In addition, the cognitive capacity of human beings might constrain researchers from generating predictions for complicated phenomena through reasoning in verbal language, especially when the processes studied involve multiple nonlinear relationships (Cronin et al. 2009). Dynamic modeling can therefore be a useful tool for researchers to derive seemingly unstraightforward hypotheses regarding dynamic phenomena and processes (e.g., Coen 2013).

Third, dynamic modeling can help extend the theory building by answering the question, "What might be if a given condition is satisfied" (Burton & Obel 2011). In particular, researchers can experiment with the dynamic model through computer-assisted simulations, which are useful when it is not possible to manipulate or measure the phenomenon directly (Aguinis & Vandenberg 2014, Harrison et al. 2007) or when it is difficult to derive the predictions mathematically. Further, using dynamic modeling to build formal theories about dynamic phenomena and processes, researchers can gain insights for future data collection. For example, by simulating the dynamic computational model, researchers can identify when theoretically important changes may happen with variables of interest and can pinpoint the data collection window as well as the length of time between repeated measures to capture them.

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DYNAMIC MODELING AS A DATA ANALYTICAL TOOL

In this section, we review three longitudinal data analytic techniques for conducting dynamic modeling with empirical data: time-series-based modeling, latent-change-score-based modeling, and functional data analysis. As we illustrate below, one common feature of these data analytic techniques is that they all offer ways to specify and estimate how the earlier state of a variable determines the later state of the same variable. This is indeed the defining feature of dynamic modeling, because time sequencing of the states offers the foundation for examining the transition rules inherent to the dynamic variable. However, these three techniques also differ in important ways, especially in terms of the research questions they address and the specific data structures to which they apply. In our overview below, we strive to clarify these differences.

Time-Series-Based Modeling

Time-series analysis consists of a group of techniques that model sequentially measured data on one or more variables (Box & Jenkins 1970). Time-series analysis recognizes and explicitly models the temporal structure of data, such as autocorrelation, trends, and seasonal effects (e.g., effect due to a holiday or a specific day of the week). Although time-series data can be continuously recorded, OPOB researchers typically have discrete time-series data measured at equally spaced intervals such as an employee's annual income over his/her life span and a company's quarterly profit and average stock price for the quarter over a 10-year period. Although time-series analysis was developed in the economics literature where firms or industries were the subjects of investigation, we foresee no difficulty for OPOB researchers to apply this technique to examine individual workers or groups (see, e.g., Fuller et al. 2003).

There are several interconnected objectives for time-series analysis, including (*a*) describing the characteristics of time-series data (e.g., trends, seasonal effects, and error), (*b*) modeling the stochastic structure of such data, (*c*) extracting critical signals in the face of noise and disturbances, and (*d*) forecasting future values based on previously observed values. Different objectives would determine the specific analytical techniques used. Because OPOB researchers are often interested in testing theory-based predictions, parametric time-series methods in which researchers assume an underlying stochastic process that generates the data and they estimate parameters to describe such data-generation processes (i.e., to test theoretically derived transition rules) may be more appropriate.

Stationarity is a key concept in time-series analysis. If a time series can be considered a realization of a stochastic model that does not change over time, then it is called a stationary time series. In simple terms, a stationary series is one without a trend or a seasonal effect and has constant variance as well as the same autocorrelation structure over time. If the stochastic structure changes over time (e.g., the means decrease and/or the fluctuations around the means increase over time), such a time series is nonstationary. Researchers may employ various methods of transformation (e.g., log-transformation, removing the trend and modeling the residuals, differencing, and using the moving average) with nonstationary time series to make them approximately stationary. Alternatively, the stochastic changes of parameters can be explicitly modeled (e.g., estimating the trend and potential seasonal effects).

In a broad sense, there are two separate (but not mutually exclusive) approaches to time-series analysis. The first is the time-domain approach, the focus of which is to model future values as a function of the current and past values. Under this approach, Box & Jenkins (1970) developed a family of models for time-correlated modeling and forecasting for univariate and multivariate time series. These models are called autoregressive integrated moving average (ARIMA) models. In the autoregressive part, the current value of the series is regressed on one or more prior values. In the moving average part, a linear regression links the current value with the white noise of one or more prior values in the series. The white noise is typically assumed to be independent and identically distributed and not directly observable. Box and Jenkins combined these two parts into ARIMA and recommended differencing nonstationary series one or more times to achieve stationarity. As such, ARIMA models (in univariate or multivariate forms) are multiplicative in nature because observed data are assumed to result from products of terms involving differential or difference equations. Box et al. (1994) and Brockwell & Davis (1991) provide mathematical details about ARIMA models.

More recent developments of the time-domain approach used additive models, among which the state-space modeling (SSM) is perhaps the most interesting tool. SSM originated in control theory in engineering (Kalman 1960) and was first applied to astronautics for tracking spacecrafts and missiles. It is flexible in handling both stationary and nonstationary time-series models. In its basic form, SSM has a state equation, which is a first-order autoregression equation. This equation defines how the current state variables are generated from past state variables. In addition, there is an observation equation that links the nonobserved states (plus observation noise) to the observed data. In the context of space tracking, the state equation determines the position of a spacecraft derived from prior positions, and the observation equation maps the position to observed information displayed on a tracking device. The state and observation equations resemble, respectively, the structural and measurement equations in structural equation modeling (SEM). As such, SSM is able to account for measurement errors, estimate relationships among latent variables, and be expressed in SEM notations (e.g., Gu et al. 2014). Commandeur & Koopman (2007), Harvey (1989), and Durbin & Koopman (2001) discussed technical details and applications of SSM.

The second broad approach is the frequency-domain approach with the primary interest pertaining to the periodic variations in time-series data. For example, spectral analysis focuses on expressing the periodic variations of the underlying phenomenon in terms of sines and cosines. Within this approach, various methods are used to decompose a time series into a trend, a seasonal effect, and a residual component. Such decomposition can also be done using the time-domain approach. As suggested by many researchers (e.g., Shumway & Stoffer 2011), these two approaches are complementary, and they often have similar results when the time series is long. When the time series is short, the time-domain approach tends to have better performance.

Regardless of the approach taken, the first step in time-series analysis is to plot the data over time and carefully examine the characteristics of data (e.g., shape, smoothness, peaks, etc.). The depicted characteristics in such a plot can suggest possible models to use in the analysis. Because researchers typically measure time-series data with certain time intervals (e.g., hourly, daily, or weekly), they need to smooth data to remove random variations; smoothing loosely means averaging in time-series data. Multiple techniques are available, such as moving average and exponential smoothing; the latter weighs older observations with exponentially decreasing weights. After smoothing, the smoothed observations are analyzed to identify the underlying stochastic models, estimating trends, and seasonal effects, and/or for forecasting future values.

Before moving on, we highlight a key difference between time-series data and the typical longitudinal data that OPOB researchers are more familiar with. In typical longitudinal data, a large sample of subjects (e.g., employees, groups, or companies) are repeatedly measured for a small number of times (e.g., daily for 10 days, monthly for a year, or annually for a decade). In this "large-N and small-T" situation, estimated coefficients are pooled within-subject estimates across the large sample of subjects. This design focuses on the between-subject relationships, and its conclusions may not be useful for understanding how a single subject behaves over time. In

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contrast, time-series analysis often deals with small-N and large-T situations in which one or a few subjects are measured repeatedly for a large number of times, such as 50 times or even 1,000 times. This type of data is also called intensive longitudinal data (Walls & Schafer 2006). In studying this type of data, researchers are interested in accurately modeling the underlying stochastic processes and/or predicting future values for the particular subject (or the particular group of subjects). Indeed, all the above-mentioned time-series techniques (ARIMA, SSM, and spectral analysis) were originally developed to examine a single-subject design. For instance, SSM can be used to track the position of a particular spacecraft, and ARIMA can be used to estimate the profit-stock price relationships for a given company. There are different ways to extend the single-subject design to a multiple-subject design. For example, multiple-group analysis can be used in which each subject is a group and parameters can be held invariant across groups. Alternatively, the time-series models can be extended to multilevel settings so that parameters are allowed to randomly vary across subjects (i.e., level-2 units; e.g., Gu et al. 2014). That said, analyzing multiple-subject time-series data is labor intensive and requires complex programming with specialized software.

The small-N and large-T design in time-series analysis has strengths of revealing how phenomena unfold over time and offering stronger causal inferences, because it focuses on intraindividual relationships and explicitly considers temporal ordering in the analysis. Fuller et al. (2003) report on an exemplar study utilizing the time-domain approach for addressing an OPOB research question. We discuss this study in more detail in the section, Dynamic Modeling in Specific Organizational Psychology and Organizational Behavior Research Areas. Despite these strengths, the obvious weakness of such a design is the potential lack of generalizability to other subjects. However, generalizability is of less concern if the goal of a study is to predict future behavior of a particular subject (e.g., a specific firm, industry, or country). Furthermore, when there are qualitative differences between subjects, researchers should by default assume heterogeneity in the intraindividual relationships (Nesselroade 1991). In reality, it is unlikely that each member in a population follows the same stochastic model that generates the time-series data (Molenaar 2004). Nevertheless, if the stochastic model fits the time-series data collected separately from several subjects, then researchers can identify these individuals collectively as a homogeneous subpopulation.

In terms of software, the major statistical packages such as R, SAS, and STATA have many useful command modules for time-series analysis (e.g., astsa in R; Shumway & Stoffer 2011). Time-invariant SSM can be estimated using many software packages such as MATLAB, SAS, and STATA. For time-varying SSM, however, researchers often need to program their own syntax to fully realize its potential.

Latent-Change-Score-Based Modeling

LCS (McArdle 2009, McArdle & Hamagami 2001) models are increasingly used by OPOB researchers to examine dynamic phenomena that unfold over time (see the bivariate LCS model in **Figure 1**). LCS models can be more user-friendly for OPOB researchers (as compared with time-series models and functional data analysis) for two reasons. First, LCS models use longitudinal data characterized as large N and small T (e.g., data collected from experience sampling methods or multiple waves of surveys), and OPOB researchers are familiar with such data and their collection. Second, LCS model estimation is based on the SEM framework, which is more familiar to OPOB researchers. In fact, LCS can be easily implemented in general-purpose SEM software (e.g., LISREL and Mplus).

LCS models explicitly define the change of a latent or manifest variable from time t to $t + 1$ as a latent variable in the SEM framework, thus enabling the incorporation of the change variable into more complex structural relationships. For a given variable X, its score at time $t + 1$ (i.e., X_{t+1}) is a

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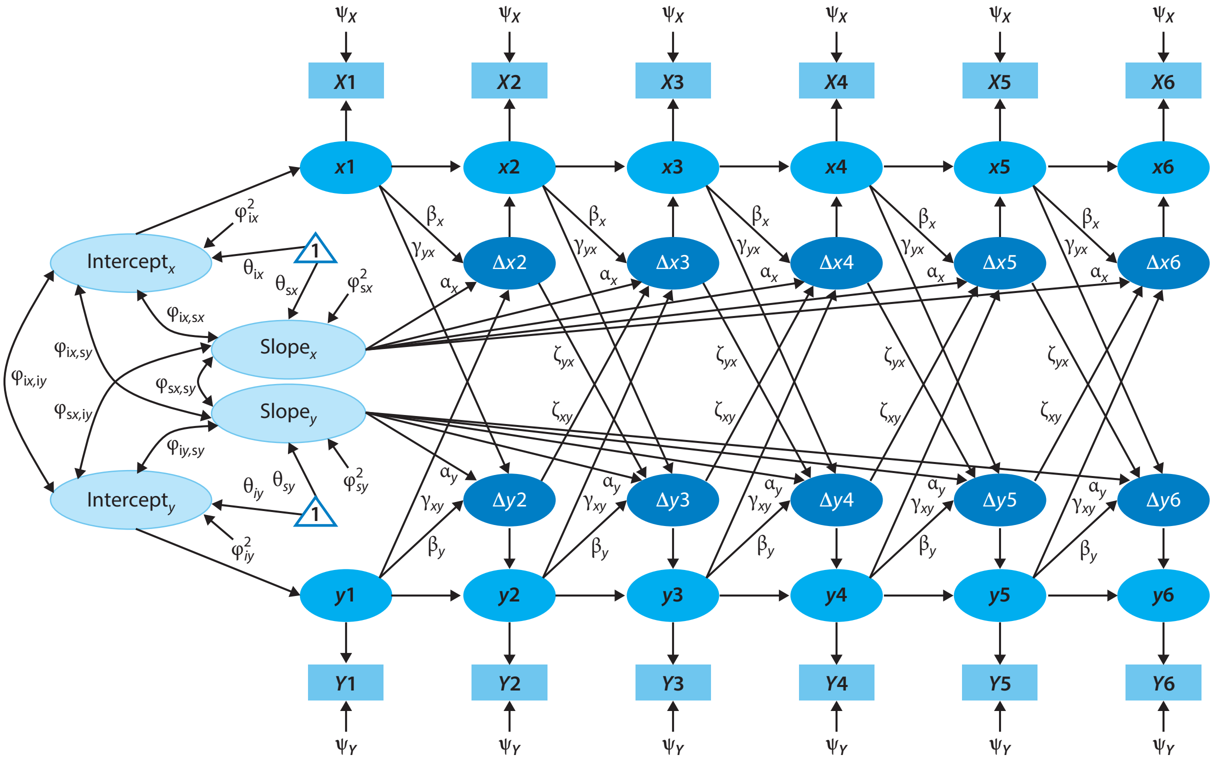

Figure 1

The bivariate latent-change-score model. Unlabeled paths were fixed to 1, whereas identically labeled paths were constrained to equality. The α_x and α_y paths were fixed at 1; all other labeled paths were freely estimated. Unlabeled variance and mean components were fixed at 0.

function of X_t and the latent change score of X from t to $t+1$ (i.e., ΔX_{t+1}). There is an initial status latent factor and a slope factor in the configuration. (The latter has a different interpretation from the slope factor in latent growth modeling or LGM.) As described by McArdle (2009), the latent change scores are predicted by several paths/effects (e.g., α, β, γ, and ξ in **Figure 1**, which we explain below). In its simplest, univariate form, the α effects carry the influence of the slope factor's mean onto each change variable and reflect a linear change (i.e., the constant change component over time in the latent change variable, which is typically fixed to 1). The β effects reflect the proportional change from t to $t + 1$ (i.e., the time-specific component that is proportional in the latent change variable). Combining the constant change, proportional change, and the initial values of the variable, univariate LCS models allow for estimating complex nonlinear trajectories. In multivariate LCS models, the γ effects link one variable's level to changes in the level of another variable, and the ξ effects link changes in a variable to changes in others. Accordingly, the latent change variable can serve as a predictor (Li et al. 2014), a mediator (Selig & Preacher 2009), and/or an outcome (Taylor et al. 2014).

After researchers have articulated research questions that explicitly examine relationships involving a change score of a variable or among the change scores of multiple variables, they can examine LCS models in several steps. The first step is to examine univariate LCS models on each of the variables of interest. In this step, the values of the slope factor means, the β effects, and the initial status of the variables are estimated. Similar to all SEM models, the conventional model fit indices (e.g., χ^2, CFI, and RMSEA) can be examined to evaluate the extent to which the proposed model fits the observed data.

The second step pertains to the examination of bivariate relationships reflected in the research questions and hypotheses. LCS models allow researchers to examine two coupling parameters (i.e., γ_{yx} is the effect of the level of X on the change in Y, and γ_{xy} is the effect of the level of Y on the change in X). However, when researchers have a strong theory to predict unidirectional influences (as opposed to reciprocal relationships), we recommend researchers directly examine a model in which one coupling parameter is fixed to zero (assuming model fit is satisfactory). In addition to the coupling parameters that link level to change, researchers may be interested in the change-to-change relationship (i.e., ξ effects).

In the third step, researchers may engage in nested model comparisons to investigate whether (*a*) a particular parameter should be held equal across time points and (*b*) a certain parameter should be fixed to zero on some or all occasions. Such procedures are similar to other SEM-based techniques. In the fourth step, researchers may be interested in extending the bivariate LCS models to trivariate and/or adding new parameters to the classic LCS model to allow the testing of more complex theoretical relations. For example, accelerated change (Grimm et al. 2013) and moderation of a change-to-change relationship (Taylor et al. 2014) are possible extensions to the classic model configurations. Furthermore, because latent change is an explicit variable, it can interact with another latent change variable or with a time-invarying variable to predict the outcomes (Toker & Biron 2012).

Regarding strengths, LCS models are more flexible than other SEM-based or multilevel modeling techniques in handling large-N and small-T data. Specifically, although nonlinear change can be modeled as quadratic or even cubic latent factors in LGMs), trajectories of change are limited to known forms. In contrast, LCS models are able to model various complex nonlinear forms of trajectory. Furthermore, different from multilevel modeling on repeatedly measured data, change is explicitly modeled in LCS, thus allowing the examination of change as a part of the theoretical model other than merely the outcome variable, such as a predictor, mediator, or moderator. LCS models define a latent change variable as the algebraic difference between the same variable at time $t + 1$ and time t. Prior work by Edwards (2002) highlighted some weaknesses of using algebraic difference between two manifest variables and proposed polynomial regressions and response surface modeling as alternatives. However, polynomial regressions can only be used to examine changes between two adjacent time points, whereas LCS can accommodate more complex models in which the change variables between multiple time points are embedded in the complex chains of relationships (e.g., as predictors, mediators, moderators, or outcomes).

Despite the strength, there are some caveats associated with LCS models. First, similar to time-series analysis, researchers using LCS models often need to measure the variables with an equally spaced time interval (e.g., 1 week or 1 day between t and $t + 1$). Although LCS could be extended to accommodate unequally spaced intervals, the classical configuration of LCS models requires that the latent slope factor has loadings of a fixed value on all latent change variables. When data have unequal spacing of intervals, researchers may rescale the latent slope factor loading to a predetermined value based on the known time intervals, and they need to eliminate the equal constraints placed on other relevant parameters involving the particular time point (i.e., the autoregressive coefficient and the β effect). When bivariate or trivariate LCS models are examined, all the variables need to be measured using the same scheme of time (equal or unequal) intervals; otherwise, the γ and ξ effects will be difficult to interpret.

Second, LCS models typically require researchers to place equal constraints on the same parameters across different time points, so that the number of estimated parameters is not beyond

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control. Such equal constraints become unrealistic when the number of repeated measures is relatively large (e.g., when $T = 20$), resulting in poorer model fit. As such, LCS models are more suitable to examine repeated measures data with a relatively small T. Third, similar to LGM and other large-N and small-T data-based models, LCS models estimate the cross-subject averages and variations of the within-subject relationships. Estimated coefficients in LCS models should be interpreted as between-person relationships. As such, researchers need to obtain a sufficiently large sample size at the between-person level to ensure accuracy of estimates.

In terms of implementation, LCS models can be estimated with most SEM software such as Mplus, LISREL, AMOS, etc. Existing applications of LCS in the OPOB literature have taken a single-level perspective. (The within-subject relationships are modeled at the person level, rendering a single-level model to handle two-level data.) The subjects are assumed to be independent from each other and there is no nesting of them in groups. This assumption can be relaxed by extending LCS models to the multilevel SEM framework to allow the key parameters in LCS models to randomly vary across groups.

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Functional Data Analysis

Functional data analysis (FDA) uses data measured densely over time, space, or other continua (Ramsay & Silverman 1997). As compared with time-series data, functional data is even more densely measured, often with intervals of milliseconds. The observed data is typically plotted over time or space in the form of a curve. In FDA, "functions" of the curves include derivatives and locations as well as extreme values. Researchers assume that certain smooth functions underlie these curves and these functions generate the observations. FDA was developed by Ramsay and colleagues (Ramsay & Dalzell 1991, Ramsay & Silverman 1997) in response to the developments in data collection techniques in recent decades. Compared to traditional analytic techniques, FDA would allow researchers to extract more time-sensitive information from the underlying smooth functions and their derivatives that are not available in traditional methods.

Unlike time-series analysis that considers observed points on a curve as data, FDA treats an entire curve as a single data point. This curve contains a set of measures along a continuum (typically time). As such, FDA has a dramatically different level of analysis as compared with other traditional methods that OPOB researchers are familiar with. With FDA, researchers are interested in variations within a single curve, and relationships between multiple curves, and the time at which certain events and the responses to these events occur. FDA allows the continuum to be multidimensional. For example, in neuroimaging the measures of brain activities can be plotted against three dimensions of space as well as time. In the following, we use time as the continuum because it is the most familiar form of dynamic modeling to OPOB researchers.

Here, an example of functional data could be helpful for readers to understand the unique questions that FDA addresses. Let us assume a researcher recruited 50 employees and measured each person's blood pressure as an indicator of stress level every 200 ms for 24 h consecutively. Each employee's blood pressure is plotted against time so that researchers have 50 curves in the plot (i.e., 50 data points). In addition to the raw observations, the researcher can plot the derivatives of the curves against time for the 24-h span. The first two derivatives, velocity and acceleration, are typically examined in FDA due to their easy interpretations.

With the 50 curves, the researcher may be interested in the following research questions. What are the distributional characteristics of the functions underlying these curves (e.g., means, variations, and covariations)? What is the difference in the timing of events in various curves? (When does a person's blood pressure peak and how does the peak differ across people?) What are the relationships between the curves' functions and covariates (e.g., employees' tenure in the company), outcomes (e.g., sales performance on that day), or functions of other curves (e.g., heart rate curve measured in the same manner)? What are the relationships between derivatives of these curves' functions? [For example, is blood pressure at a given time point (the level) influenced by how quickly blood pressure changes (the first derivative) and the magnitude of acceleration or deceleration in blood pressure change (the second derivative)?] The final question is about differential equations: Where is the level or a derivative of a curve at a certain time linked to other derivatives of the curve.

The first step of conducting FDA involves smoothing. Even though functional data is recorded in a dense manner, it is still discrete. Therefore, smoothing is needed to represent data as a continuous function of time to evaluate velocity and acceleration of change and reduce noise. Smoothing can also help remove measurement error and other forms of local disturbances. After smoothing, researchers can set aside the observed data and use the estimated (smoothed) curves for further analyses.

The second step is registration. Curves can differ along the y-axis and/or along time (the x-axis). The former difference is called amplitude variability and the latter, phase variability. Registration involves shifting the curves so that all curves are aligned with time. Depending on the research question, amplitude variability may or may not be meaningful, and thus shifting along the y-axis is not always performed.

When conducting analysis, researchers want to quantify variability within a given curve and across the sampled curves. In other words, both between-subject and within-subject relationships are examined. FDA handles large-/moderate-N and large-T situations because a curve reflects large T and researchers can take a sample of curves from a large population of curves. This is similar to traditional multivariate models where a sample of subjects was examined. In fact, the conventional multivariate analytic tools (such as correlation, principle component analysis, analysis of variance, and linear models) all have their counterparts developed in functional data settings (e.g., Guo 2002). A key difference in FDA settings is that the conventionally estimated coefficients or effect sizes themselves become functions of time (e.g., a linear regression coefficient becomes a curve). A unique analytical tool of FDA is differential equation modeling. As illustrated above, a differential equation expresses a relationship between a function and one or more of its derivatives. For example, the second derivative of a variable can be regressed upon the variable itself as well as the first derivative. Hu et al. (2014) extended differential equations to allow moderators, and they provided an example of using such a method to examine emotional eating behaviors.

Similar to the available software for time-series analysis, major software packages have all embraced the standard FDA techniques including R, S-Plus, and MATLAB. Comparing FDA with time-series analysis, we note that smoothing is an essential task for both, although the two methods tend to use different methods for smoothing. FDA tends to use nonparametric methods, whereas time-series analysis uses parametric methods. Another difference between FDA and time-series analysis is the sampling rate (i.e., how frequently researchers measure the variables). Time-series data tend to have lower sampling rates (i.e., lower resolution of the curve). Insufficient sampling rates can reduce the degree of smoothness of curves, thus hindering the identification of the underlying stochastic model for obtaining derivatives in FDA. In terms of exemplar sampling rates, FDA has been applied to analyze neuroimaging data where the sampling rate is at the millisecond scale and to handwriting data where the position of the tip of a pen was measured with a frequency of 200 Hz. In fields that are more closely related to OPOB, FDA has been used to examine the maintenance or changes in dysfunctional lifestyles (e.g., smoking and emotional eating; Hu et al. 2014) by collecting data at the behavioral level multiple times a day. In OPOB research, recent studies have started to collect intensive longitudinal data. For example, Gabriel & Diefendorff's (2015) experiment used a call center simulation to measure 76 participants' felt

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emotions and emotional labor variables every 200 ms, and recorded these variables for approximately 4.5 minutes for each participant. Although these authors used multilevel modeling and cross-lagged panel data analysis, their data are perfectly suitable for FDA (with the research questions focusing on when an event occurs and the differences in the occurrence timing across participants) and time-series analysis (with the research questions focusing on intraindividual causal effects).

DYNAMIC MODELING AS A THEORY-BUILDING TOOL

In this section, we review three computational modeling approaches that can be used for building dynamic models that specify theories to explain dynamic phenomena and processes in OPOB research. As we illustrate below, the choice of specific computational modeling approach depends on the specific research questions and the phenomenon examined. Our review mainly uses examples from recent published dynamic modeling research in OPOB research (for a collection of earlier dynamic modeling OPOB studies, see Ilgen & Hulin 2000). Readers who are interested in learning the technical details of conducting dynamic modeling studies or examples in organizational theory and strategy research can refer to other sources (e.g., Davis et al. 2007, Gilbert & Troitzsch 2005, Lomi & Larsen 2001, Sterman 2000). Toward the end of this section, we also discuss caveats for using dynamic modeling for theory building.

Agent-Based Modeling

Agent-based modeling is one of the earliest dynamic modeling methods introduced into management research and has been used in strategy and organization theories research. For example, agent-based modeling has been used in research on organizational learning, organizational culture, and innovation (e.g., Carroll & Harrison 1998, March 1991). However, it is not until recently that this approach is recognized by OPOB researchers as a useful tool for studying the emergent processes at the micro and meso levels (Kozlowski et al. 2013).

Agent-based modeling is particularly suitable for understanding OPOB phenomena that share the following features (Fioretti 2013). First, when the structure of interactions among multiple agents (also called actors) in a dynamic social system is of particular interest, agent-based modeling can be a helpful theory development tool. For example, researchers can model whether the structure of interaction among agents in multiple teams or in a multiteam system relates to dynamic processes and outcomes in the system (e.g., Coen 2013). Second, agent-based modeling is particularly suitable for understanding the history and timing of emerged collective states (e.g., group norms, shared mental models, collective efficacy, psychological safety; Dionne et al. 2010) from interactions among individual agents (e.g., individuals, positions, component teams). In other words, agent-based modeling can help describe and understand the shift of qualitative statuses over time (e.g., a property of a collective develops from nonexistent to being shared among multiple lower-level units).

Agent-based modeling carries out theory building by using simulated "agents" to represent actors in social interactions within a given environment. These agents have a set of attributes and self-contained rules (i.e., the content of dynamic theory) that control their internal information processing and external behaviors (Gilbert & Troitzsch 2005). Information flows into the agents through interactions with other agents and from other components of the environment (e.g., interventions, policy changes). The agents process the information they received, make decisions, and react accordingly. Outputs from the agents, such as actions and communications with other

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agents, can affect subsequent interactions among agents and the external environment over time.

Agent-based modeling can be used to represent several fundamental psychological concepts and processes over time (Fioretti 2013, Gilbert & Troitzsch 2005); for example, information enters agents through perception processes. Therefore, it is possible to represent knowledge (i.e., truth or facts in the environment), belief (i.e., agents' internal representation of the environment), and inference (i.e., processing results of agents' beliefs) separately. For example, in March's (1991) model, agents hold "beliefs" about the organizations, which might be different from the factual "knowledge." Agents can also be specified to engage in goal-directed processes following certain rules, which represent the theoretical construct of agency or intention. For example, Vancouver et al. (2010a) use agents to represent newcomers who, driven by the goal of achieving role clarity, "want" to obtain organizational knowledge. Furthermore, communication or information exchange between social actors can be specified as between-agent interactions. Sometimes these interactions can be simplified by assuming that the information passed from one agent to another remains identical. In terms of the scope of interaction, it is possible to assume that all agents interact with all others during each time unit. More structured information exchange patterns can also be represented. For example, in cellular automata models (a specific type of agent-based model), agents are positioned as a lattice and they can only interact with neighboring agents. Finally, attributes of the context where the interactions among the agents happen can be studied as well. For example, information exchange might be bounded by formal organizational structure and communication technologies used by the organization, which can be represented as different forms of information exchange functions (e.g., Kane & Alavi 2007).

As with any other computational models, agent-based models can be programmed and simulated using general purpose programming language (e.g., C++) or in general purpose software packages with programming capabilities (e.g., MATLAB or Excel). However, certain structures can be repeatedly used or adapted in similar models, especially when the models developed address a series of related questions (e.g., March 1991, Kane & Alavi 2007). Therefore, several user-friendly platforms have been developed for agent-based modeling, including NetLogo (**https://ccl.northwestern.edu/netlogo/**), Repast (**http://www.repast.sourceforge.net**), MASON (**http://cs.gmu.edu/~eclab/projects/mason/**), Swarm (**http://savannah.nongnu.org/projects/swarm**), MaDKit (**http://www.madkit.net/madkit/**), Brahms (**http://www.agentisolutions.com/index.htm**), and CORMAS (**http://cormas.cirad.fr/indexeng.htm**) (Fioretti 2013, Gilbert & Troitzsch 2005). Most of this software is free and has documented examples, including social science applications. For example, one of the most user-friendly software for agent-based modeling, NetLogo, allows researchers to use a graphical interface to build agents that interact on a grid. NetLogo also has a library in which users can access, learn, and modify preprogrammed models.

System Dynamics Modeling

System dynamics modeling is often used to build theories that explain the dynamic changes in systems (e.g., an individual, a dyad, a team, a multiteam system, an organization, etc.) over time (Taber & Timpone 1996). As compared to agent-based models, system dynamics models do not necessarily have multiple agents. Sometimes, it is the changes within a single agent that is of theoretical interest. In addition, system dynamics modeling is more concerned about the maintenance of or regulation toward the stable state (or equilibrium) than agent-based modeling (Davis et al. 2007, Rudolph & Repenning 2002). For example, researchers using system dynamics approaches might be particularly interested in examining the timing of abrupt changes and how

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long it takes for the system to recover to its normal state, as well as the time interval between cycles of states.

System dynamics models often specify theories about state variables (also called stock variables or level variables). These are variables that have "memories" of states at previous time points, such as task performance, acquired knowledge, and retirement saving. State variables start from given initial levels, which are either specified as exogenous variables or are influenced by other variables in the model. Depending on the transition rules captured by the theory, the specific form of change of the state variables from t to $t + 1$ can be specified as a fixed value, a set of values that are effective within certain time periods, or a function of other variables in the model. Through simulating the dynamic model, researchers can observe the change trajectories and the end state of the state variables. In addition, state variables can also influence other variables in the model. Thus, simulation results from system dynamics modeling allow us to examine how the trajectories of the state variables and other variables coevolve over time (Vancouver et al. 2010a). State variables can be specified mathematically using differential equations or difference equations. Differential equations are used when the state variable changes over time (e.g., retirement saving) continuously, whereas difference equations are used when the changes are discrete (e.g., number of tasks accomplished).

System dynamics models typically include a series of causal loops (i.e., variable X influences variable Y which in turn influences variable X). Therefore, system dynamics modeling is particularly suitable for studying OPOB phenomena that involve complex circular causal relationships, such as feedback seeking and acquired knowledge (Vancouver et al. 2010a), stress and coping (Edwards 1992), and effort and task state (Vancouver et al. 2010b). In addition to state variables and causal loops, system dynamics models also include representation of attributes of the environment with which the system interacts. For example, random disturbances from the environment can be represented as shocks to the system.

System dynamics models often use negative feedback loops to represent the state variables, circular relationships, and interactions between the system and the environment (**Figure 2**). In the negative feedback loop, the current state of a state variable (v; e.g., the current amount of acquired knowledge) is perceived by the system through an input function. Perception of the current state (p) is influenced by the actual current state and a bias factor (b). The system aims to regulate the state variable toward the desired state (p^*; e.g., the desired amount of knowledge). The system compares p to p^* through the comparator, which might detect a discrepancy (d) between them. The comparator function is often asymmetric, which generates a zero when the desired state is equal to or less than the perceived state. In addition to discrepancy, output (o; e.g., effort spent on acquiring knowledge) is influenced by an amplifying or attenuating factor called gain (k). Output in turn changes the current state of the state variable. How fast the change happens over time is influenced by the rate factor (r; e.g., cognitive ability). The current state of a variable is also influenced by unexpected shocks from the external environment, called disturbances (D). When dynamics in the state variable are modeled in continuous time, the current state v at time t can be specified as an integral function (see **Figure 2**; Vancouver et al. 2010b). In a negative feedback loop, the process that goes through input, comparator, and output functions together forms the basic theoretical building block. This basic structure can be expanded to more complex systems that include multiple subsystems and can control a set of state variables (e.g., Vancouver et al. 2010a). In addition to this type of negative feedback loop, systems dynamic models can also represent positive-reinforcing loops (Rudolph & Repenning 2002).

In addition to general-purpose programming languages, numerous software have been developed specifically for system dynamics modeling, including STELLA (**http://www.iseesystems.com/**), PowerSim (**http://www.powersim.com/**), and Vensim (**http://vensim.com/**) (Gilbert

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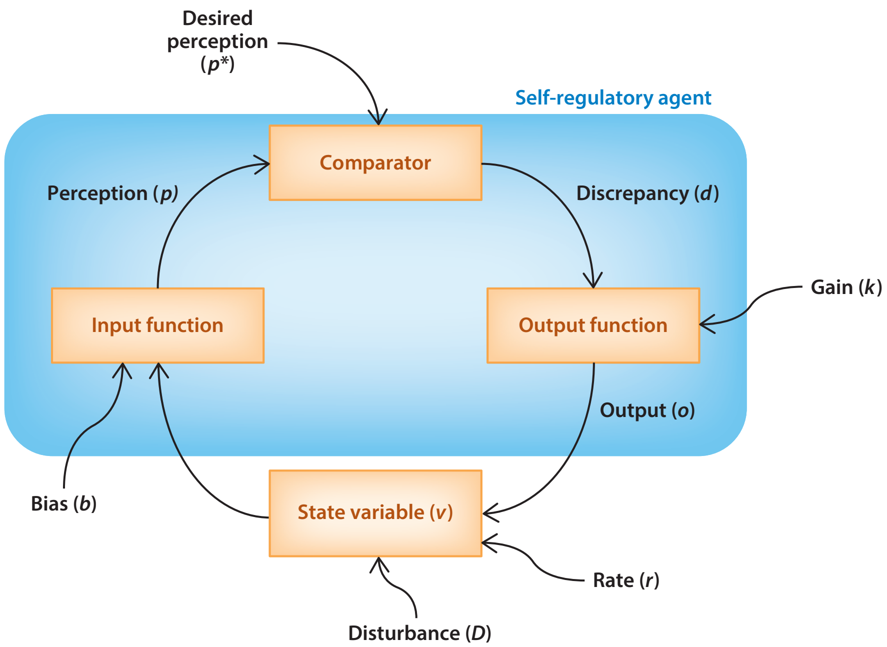

Figure 2

Negative feedback loop in self-regulation theory. Variables illustrated in this model are formally specified by the following equations: $p = v + b$. If $(p^* - p) > 0$, then $d = (p^* - p)$; otherwise, $d = 0$, $o = kd$, and $v_t = \int_{t_0}^{t} (ro + D)dt + v_{t_0}$. Figure adapted from Vancouver et al. (2010b).

& Troitzsch 2005). For example, Vensim allows researchers to build the model using a graphical interface. Simulation results can be viewed as graphs in Vensim, and numeric values of the simulation results can be exported into other software including Excel. In addition, Vensim Professional has a built-in optimization module, which can compare the simulated data to imported data from human participants and estimate the optimized values of selected input factors via differential equations that are similar to those used in FDA procedures or nonparametric methods.

Hybrid Dynamic Modeling

In addition to agent-based modeling and system dynamics modeling, other dynamic model structures could also be applied to OPOB research, such as applying connectionist models to implicit leadership theory research (e.g., Hanges et al. 2000), using knowledge-based systems to study decision makers (e.g., Taber 1992), using discrete event models (Kreutzer 1986) to study customer service events, and applying genetic algorithms to study team performance optimization (e.g., Kennedy & McComb 2014). Each of these modeling approaches is more suitable for a specific type of theory building, depending on the research questions and the central mechanisms specified by the intended theory.

Sometimes a research question cannot be answered by using only a single modeling approach. For example, when researchers try to integrate theoretical mechanisms from different perspectives, the processes to be integrated might have very different basic structures and underlying mechanisms. In this case, it is necessary for researchers to adapt existing modeling approaches and develop customized hybrid models (Davis et al. 2007). Carroll & Harrison (1998) represent one such research example. In this study, the authors examine how organizational culture heterogeneity is driven by three interrelated dynamic processes over time: newcomers joining the organization, socialization processes, and ongoing turnover. Each one of these processes involves theoretical relations that are difficult to specify in conventional verbal theories. In addition, these dynamic processes involve both the interactions among multiple agents and changing memberships of the agents based on their relations with the collective. These processes are difficult to specify using a simple agent-based or systems dynamics modeling approach. By using hybrid dynamic modeling, Carroll & Harrison (1998) were able to represent the complex underlying mechanisms and simulate their interactions over time.

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Some Caveats of Using Dynamic Modeling for Theory Building

We end this section by discussing several caveats when using dynamic modeling for theory building. First, previous researchers (Harrison et al. 2007, Kozlowski et al. 2013, Taber & Timpone 1996) have cautioned that it is easy for computational models to be unnecessarily complicated. This is not a limitation of dynamic modeling itself, as it is up to the researchers to decide the level of abstraction from the phenomenon to the model. However, given the power and flexibility of computational modeling, sometimes researchers are tempted to create variables for every possible theoretical mechanism that may explain the dynamic phenomena. Nevertheless, theory building in nature is an activity to create parsimonious abstractions of reality. Thus, dynamic theory building should include the procedure of comparing the proposed model to more or less complicated models (see Vancouver et al. 2010b for an example). Simulation-based sensitivity analysis can also be used to determine whether a specific theoretical component is necessary to maintain the theory's explanatory power.

Second, because dynamic theory building relies on computer programming and simulation, it is often difficult to comprehensively report the model. Some researchers have chosen to report the codes directly obtained from the software (e.g., Vancouver et al. 2014). Other researchers chose to report the key mathematical functions included in the model (e.g., Carroll & Harrison 1998). When there is insufficient information about the model specification, it is difficult to evaluate the modeling procedure and for later research to replicate and extend the models. It is also possible for programming errors to be overlooked when the codes used for simulation are not fully reported. As Harrison et al. (2007) pointed out, the "ultimate test is whether other simulators can replicate the simulation findings" (p. 1242). Considering there are ample resources available for researchers to host research materials online (e.g., personal websites, journal websites), we encourage researchers to make their programming codes of the models and simulation procedures publicly available.

Third, researchers should be careful about statistically analyzing outputs derived from simulating the computational model. How to interpret the outputs from simulating computational models depends on the research question. For example, either outputs from a specific time window or the end state can be analyzed (e.g., Dionne et al. 2010). Either raw outputs or aggregated values can be analyzed as well (e.g., Vancouver et al. 2010b). It is also possible to use statistical procedures to analyze simulated data (e.g., with time-series or FDA procedures). However, when the simulated data are from nonlinear processes, linear models may not be appropriate. Therefore, typical SEM-based techniques may not be appropriate for this practice. In addition, because the sample size of simulated data can be large, significance testing results may not be as meaningful and informative as reporting effect size measures.

Finally, a stand-alone dynamic theory-building study can be limited in external validity (Burton & Obel 2011). However, this limitation can be overcome by coupling computational modeling with experiments, archival data analyses, and other empirical studies (for examples of simulation-human data comparison, see Vancouver et al. 2010b, 2014). Again, computational dynamic models are merely theoretical models. Whether they are valid representations of the dynamic phenomenon in reality needs to be tested empirically.

DYNAMIC MODELING IN SPECIFIC ORGANIZATIONAL PSYCHOLOGY AND ORGANIZATIONAL BEHAVIOR RESEARCH AREAS

Emergence Processes at the Team and Organizational Levels

Kozlowski and colleagues (Kozlowski & Chao 2012, Kozlowski & Klein 2000, Kozlowski et al. 2013) advise researchers to take a dynamics-focused approach to studying bottom-up emergence phenomena in OPOB research. As they point out, it is difficult to use quantitative methods that are most commonly used in existing OPOB research to study emergence phenomena, because emergent phenomena are multilevel and process oriented, and they take time to unfold. These characteristics of emergence require theories to specify interactive dynamic processes among lower-level units and emerged higher-level properties at the same time. On the basis of a review of existing theoretical and quantitative empirical research on emergence, Kozlowski et al. (2013) suggested that dynamic modeling, especially agent-based modeling, can be a primary method for studying how psychological properties of the collective (e.g., climate, norm, cohesion, shared mental model) emerge from interactions among individuals and their personal characteristics.

Specifically, Kozlowski et al. (2013) outlined that a dynamic computational model on emergence would need to specify the initial states of the agents in a given environment and a set of theory-based or evidence-based rules (e.g., "if-then" statements) that direct the interactions among agents within the environment. By simulating the dynamic model, researchers can observe how collective level properties unfold over time. Kozlowski et al. (2013) also pointed out that to empirically study emergence processes requires collecting intensive longitudinal data. Traditional self-report-based questionnaires are not ideal due to constraints on human participants (e.g., fatigue, intrusiveness, etc.). New ways of collecting empirical evidence (e.g., analyzing digital traces) might be more effective. Furthermore, traditional statistical tools may not be appropriate for testing data collected from intensive longitudinal data either, as the trajectories of the study variables may not be monotonic and cannot be easily specified by a commonly known functional form (e.g., linear, quadratic). This calls for the use of differential equation-based statistical methods, such as FDA, which we reviewed earlier.

A more specific example is Dionne et al.'s (2010) study on the emergence of shared mental models and the role of leadership in the emergence process. This study took an agent-based modeling approach. Previous research suggested that the formation of shared mental models among team members goes through multiple stages and is driven by team members' domains of expertise (McComb 2007). Dionne et al. specified a dynamic model in which agents represent team members and share their individual opinions with others, evaluate each other's opinions, and modify their own understanding of the team based on new information obtained. This process iterates over time. Furthermore, in this dynamic model, different types of leadership conditions were represented by different networks linking the agents. Specifically, LMX is specified by a network with only in-group members connected to the team leaders, whereas participative leadership is specified by a network with fully connected ties among team members. Each agent starts from holding nearly perfect knowledge in a domain and almost no knowledge in other domains. Highly differentiated domains of expertise in a team are characterized by starting with the least similar knowledge held by team members. As the process unfolds, team mental models emerge and

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teams' collective performances in problem solving change (as a function of the knowledge domain change).

Simulation results from Dionne et al. (2010) showed that shared mental models emerge faster than LMX when team leadership is characterized by participative leadership. When team members' domains of expertise are highly differentiated and mutual interest is strong, team performance improved more (comparing end state to beginning state) under participative leadership conditions than LMX conditions. However, when team members' domains of expertise are not differentiated or mutual interest is weak, team performance is improved more when team leadership is under LMX conditions than under participative leadership conditions. This research demonstrates that dynamic modeling can be a useful tool for unpacking the emergence process and comparing different processes under different conditions of team member characteristics and leadership characteristics. In future research, extended dynamic models could be specified to integrate multiple emergent processes. For example, it would be interesting to understand under what conditions one collective cognitive state (e.g., shared mental model) emerges before another (e.g., transactive memory system), as well as how collective cognitive states adapt simultaneously over time (Kozlowski et al. 2013).

Learning, Decision Making, and Motivation

In OPOB research, dynamic modeling has also been used for theory building on topics related to learning, decision making, and motivation. For example, Rudolph et al. (2009) took the system dynamics modeling approach and built a theoretical model of action-oriented problem solving to integrate the interpretation and choice processes that had been separately examined in the sense-making literature and decision-making literature, respectively. Their model uses doctors solving problems in an operating room context. Specifically, actions taken by doctors (i.e., problem solvers) feed confirming or disconfirming information about the current leading diagnosis to the interpretation loop. The interpretation loop determines the level of plausibility of leading diagnosis (i.e., the state variable). While executing the action that follows the current leading diagnosis, doctors continue interpreting available information and evaluating alternative diagnoses. These interrelated processes unfold over time until the leading diagnosis is the correct diagnosis.

Simulation results from Rudolph et al. (2009) suggested that the processes of interpreting, acting, and cultivating alternative diagnoses interact to influence the problem solving process. Information generated from one process serves as input to other processes. Furthermore, effectiveness in this type of action-oriented problem solving is influenced by problem solvers' ability to vary the pace of the interrelated processes in relation to the changes in the environment. Contrary to common belief that reinforcing leads to fixation, the simulation results showed that reinforcing the current course of action can be beneficial for problem solving when it is faster to generate alternatives than to evaluate the current course of action. In addition to these relationships, the modeling results offered several propositions to be tested empirically in the future.

In a series of studies, Vancouver and colleagues (e.g., Vancouver 2008; Vancouver et al. 2010a,b, 2014) proposed and tested dynamic theoretical models on decision and motivational processes in goal pursuit. Vancouver et al. (2010b) examined how individuals pursue multiple performance goals simultaneously. This study was inspired by empirical data generated in Schmidt & DeShon's (2007) laboratory experiment on multiple-goal pursuits. They found that individuals preferred to work on the task with a larger discrepancy between the current state and ideal state (i.e., goal) in the earlier part of the multiple-goal pursuit session. However, as time gets closer to the prespecified deadline, individuals might switch their preference to the goal with a smaller discrepancy between the current state and ideal state. To account for this reversing relationship between discrepancy

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and choice, Vancouver et al. (2010b) drew on self-regulation theory and extended the concepts of valence and expectancy from static to dynamic forms. Their computational model specified that the choice of which goal to spend effort on at a given time point is decided by comparing the utilities of the two competing goals. The utility of each goal is modeled by multiplying discrepancy, expectancy, and incentive at a given time point. Through an optimization procedure, the study fit the dynamic model to the empirical data collected in Schmidt & DeShon (2007). Model-data fit statistics suggest that the dynamic model fits the empirical data well. In addition, variances in the time-invariant parameters in the model could account for individual differences among participants when the effect of discrepancy on task choice reversed.

Although Vancouver et al. (2010b) illustrated how dynamic modeling could help deepen our understanding of complicated motivational processes, their model did not take into account the role of learning. To incorporate learning processes into the dynamic model on goal pursuit, Vancouver et al. (2014) drew on the delta-learning rule used extensively in cognitive science research on adaptive human behaviors. Specifically, individuals could learn about the efficiency of their actions on goal achievement. This learning function is influenced by individual differences in adjusting their expected efficiency when receiving new information and initial expected efficiency. Vancouver et al. (2014) also included individuals' internal representation of environmental disturbances in the model. Individuals have initial expected disturbances and adjust the expected disturbance level when new disturbances occur. Expected disturbances in turn influence individuals' anticipated discrepancy. Vancouver et al. (2014) fit the dynamic model with these two learning functions to data collected from human participants in DeShon & Rench (2009) and Schmidt & DeShon (2007) and found support for the model.

In future research, computational models could be specified to examine learning and motivational processes in larger organizational units and to integrate microcognitive mechanisms with theories on interpersonal processes. For example, it would be interesting to integrate socialization, leadership, and self-regulation theories to examine how newcomers develop self-identities and relationships with their direct reports and other organizational members over time (Vancouver et al. 2010a, Zhou & Wang 2015). Future research could also extend prior work on learning (e.g., March 1991, Kane & Alavi 2007) and examine how learning processes unfold at different levels and interact among each other. Dynamic data analytic tools (e.g., time series and FDA) can also be used to estimate parameters in formal models and test relationships derived from computational modeling. For example, DeShon (2012) illustrated how the relationships between self-efficacy and performance, two key variables in a self-regulatory system, could be estimated by fitting vector autoregressive models to time-series data. Future research could follow DeShon's approach to estimate recursive relationships among variables in larger self-regulatory systems.

The limited empirical research on dynamic processes in learning and motivation has almost exclusively collected data from student samples in lab settings (e.g., Schmidt & DeShon 2007). Besides the generalizability problem, certain phenomena cannot be easily reconstructed in the lab without losing psychological fidelity (e.g., newcomer adjustment process). Therefore, field studies are needed to test dynamic theories in this area. To overcome limitations in self-report bias, we recommend that future research collect data from other sources (e.g., digital traces collected through wearable devices or other big data sources; Beal 2015).

Work-Related Stress Process

Although dynamic modeling in the form of theory building had not previously been used in studying work-related stress processes in OPOB research, two influential theoretical models were proposed in the past two decades. In particular, Edwards (1992) drew on the psychological control

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theory and proposed a cybernetic model of stress, coping, and well-being. Edwards argues that stress occurs when individuals perceive a discrepancy between perceived current state and ideal state and specified reciprocal relationships in stress processes (e.g., coping influences well-being, which in turn influences coping). Beal et al. (2005), however, applied the affective event theory to explain how affect and stress influence performance over time. Their model focuses on the process of allocation of regulatory resource, which is influenced by multiple interdependent concurrent on-task and off-task processes. Although both of these models describe dynamic processes in stress, they are both verbal theories without formal (i.e., mathematical or logical) specifications. Moreover, most of the existing empirical tests of these two models have only examined one or two specific directional relationships in the models (e.g., whether negative emotion relates to affective delivery in the same performance episode; Beal et al. 2006) rather than the reciprocal relationships (e.g., how affective states and task behaviors as two ongoing processes influence each other). Therefore, it may be fruitful for future research to use dynamic modeling to examine more complex theoretical processes and build more comprehensive dynamic theories about work-related stress processes.

In terms of empirical research, although some recent work-related stress studies continue to use cross-lagged panel designs (e.g., Hülsheger et al. 2010, Meier & Spector 2013), dynamic modeling has started to be applied more extensively, especially with the developments of experience sampling methodology (Beal 2015). For example, Fuller et al. (2003) tested a dynamic model about the relationships among stressful events, mood, strain, and job satisfaction over multiple days. These authors argued that mood, strain, and job satisfaction fluctuate due to the occurrence of various events in the work environment. In addition to the same day effects, these authors were also interested in examining the temporal sequence among these four variables, such as the effects of mood on job satisfaction on the following day. Data from a sample of 14 university employees were collected on a daily basis over the course of an academic semester. Time-series modeling results suggested that strain accumulated over time throughout the semester, although the severity of events did not change significantly. After accounting for the effects of serial dependency, the findings suggested that stressful events had indirect effects on job satisfaction on the same day through strain. In addition, positive mood was positively related to job satisfaction on the subsequent day. Interestingly, the study also found that stressful events were negatively related to strain and positively related to job satisfaction on the following day. Fuller et al. explained that this could be considered a recovery effect of events that might have resulted from coping and self-regulation mechanisms. More recently, researchers have applied LCS-based models to examine work-related stress processes (e.g., Christie & Barling 2009, Huang et al. 2013, Jones et al. 2013, Smith et al. 2013, Taylor et al. 2014), which offer better causal inferences in terms of estimating level-to-change and change-to-change effects.

Future research on work-related stress can use computational modeling to further integrate and extend stress theories. For example, dynamic models could be specified to integrate research on recovery processes and self-regulatory resource depletion processes. An integrated model could also be developed to examine how various individual differences influence different aspects of stress processes. In addition, dynamic models are needed to better explicate stress processes that span and transit among multiple life domains (e.g., work and family). Another question that can be addressed by a dynamic modeling approach is how work-related stress cumulates and progresses (e.g., how it emerges into chronic occupational health problems).

Future studies could also apply FDA for testing theories on complicated nonlinear stress processes. As mentioned earlier, OPOB research has started to collect intensive longitudinal data about emotions that can be analyzed with FDA rather than manually collapsing and removing meaningful variances (e.g., Gabriel & Diefendorff 2015). In addition to affective processes, research on health-related behaviors in the workplace (e.g., smoking, drinking, and eating) can also use FDA, given "true" event-level data on these behaviors likely consist of numerous observations from each individual.

CONCLUSION

This article aims to achieve four goals: to provide an overview of the general forms of dynamic modeling in OPOB research, to discuss three data analytic techniques for conducting dynamic modeling with empirical data, to introduce three dynamic modeling approaches for building theories about dynamic phenomena and processes, and to highlight several OPOB research areas as examples where dynamic modeling has made important contributions either in terms of building theories or examining empirical data, or both. Due to space limitations, we are not able to fully explore the richness of the topic area or offer sufficient technical details for various ways of conducting dynamic modeling. Nevertheless, we hope that the materials presented here offer a useful illustration of the general approach and utility of dynamic modeling, facilitating researchers' use of dynamic modeling and subsequently contributing to future progress in our field.

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