Many organizational phenomena are dynamic in nature, meaning that they evolve over time (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013; Lord, Diefendorff, Schmidt, & Hall, 2010; Neal, Ballard, & Vancouver, 2017; Wang, Zhou, & Zhang, 2016). Examples include individual motivation and performance, team cohesion and effectiveness, and organizational culture. There are many theories that seek to describe the processes that produce changes in these phenomena. Examples include Self Regulation Theory (Carver & Scheier, 1998), Conservation of Resources Theory (Hobfoll, 1989), the Reoccurring Phase Model of team processes (Locke & Latham, 1990), and the Cultural Dynamics Model (Hatch, 1993). However, dynamic theories are difficult to test. This is because the processes described by these theories can be difficult to directly observe or measure, and there may be a mixture of different processes involved that unfold in different ways for different people, or in different contexts. To further complicate matters, there may be different processes acting at different levels, that unfold over different time scales.

Currently, there are several approaches to developing and testing dynamic theories that are advocated. One common approach is to use a statistical model such as the latent growth curve model, cross lagged panel model, or the latent change score model. These models can be implemented within the structural equational modelling framework by imposing various constraints, and can be used to examine factors that influence the trajectory of variables over time, as well as factors that can influence the change in the level of variables at each point in the time series.

structural equation modelling

A wide range of statistical procedures have been used to analyze dynamic processes, such as latent growth curve models, cross lagged panel models, and latent change score models. Many of these procedures have been developed within a structural equation modelling (SEM) framework that combines multivariate regression with the measurement of latent constructs. By imposing various model constraints, the general framework has been extended to encompass temporal designs such as latent growth curves and discontinuous change models. However, there are a number of challenges associated with these statistical approaches. First, the constraints required to model dynamics can be complex and non-intuitive. Second, these models often require a unique variable to be specified for each observation, making it difficult to model time series’ with more than a modest number of observations per participant (Wang et al., 2016). Finally, the broader challenge with this approach is that these statistical models do not directly operationalize the processes described by the theory (Collins, 2006). Thus, these models only provide an indirect test of the theory.

An alternative approach that has been championed is computational modelling, which refers to the practice of articulating theory in the form of mathematical equations and/or computer code and evaluating the dynamic properties of the theory by simulating the model. Advantages of this approach include the ability to a) directly and transparently represent theoretical assumptions, b) generate quantitative predictions regarding how the process plays out over time, and c) demonstrate that a core set of assumptions is sufficient to produce a particular behavior or empirical phenomenon (commonly referred to as establishing “generative sufficiency”). However, computational models are often tested in relatively indirect ways. Computational models are typically evaluated by examining whether the output of the model corresponds to a trend reported in previous research. However, the degree of correspondence between the model output and previous research.

might just be assessed visually.

Another approach that has been advocated

A wide range of statistical procedures have been used to analyze dynamic processes, such include multilevel regression, latent growth curve models, cross lagged panel models, and latent change score models. Many of these procedures have been developed within a structural equation modelling (SEM) framework that combines multivariate regression with the measurement of latent constructs. By imposing various model constraints, the general framework has been extended to encompass temporal designs such as latent growth curves and discontinuous change models.

But quantitative tests

A complimentary approach

However, computational modelling has primarily been used for theory development, rather than theory testing.

establish “generative sufficiency”, that is

First, the use of computational modelling has become increasingly common

Computational modelling. The benefits of computational modelling. Directly represent the processes thought to be operating. Generative sufficiency. However, a number of challenges associated with the way this approach has been used. First, models have not been fit to data, making it difficult to determine how well the model actually accounts for the data. Also, difficult to quantitatively compare competing alternative models.

Need to embed a computational model within parameter estimation algorithm.

To test a dynamic theory, a statistical model must reflect the processes described by that theory (Collins, 2006).

Although these models capture important dynamic processes, they are limited in a number of ways. First, the constraints required to model dynamics can be complex and non-intuitive. Second, alternative models can be difficult to specify. Third, these models often require a unique variable to be specified for each observation, making it difficult to model time series’ with more than a modest number of observations per participant (Wang et al., 2016). Finally, using standard frameworks, it can be difficult to model variability in dynamic processes between individuals, or the interaction of different processes within the same individual.

For example, self-regulation theory might predict that people will allocate increasing effort to a task as a deadline approaches. This proposition might be tested using a latent growth model in an SEM framework such that individuals show a linear increase in effort over time. The SEM model might be extended to include different patterns of change (e.g., quadratic or other non-linear patterns) and variations among individuals in the specific pattern. However, self-regulation theory also proposes that a higher-level control process regulates how the person responds to difficulties encountered in goal progress. People can respond to difficulty in multiple ways, including changing strategy, extending the deadline, adjusting the goal or abandoning the task (Neal, et al., 2017). Moreover, the point at which these responses are triggered might also differ among individuals. The specification of the model therefore becomes increasingly complex in a standard statistical framework.

In this paper, we propose a Bayesian approach to modeling dynamic processes that is more intuitive, flexible, and comprehensive than the more common extensions of the SEM framework. Under this approach, there is virtually no limit to the form of the model that can be specified. The flexibility of this approach makes it possible to construct statistical models that map more directly onto psychological theory. This enables a closer coupling between theory and model that facilitates theory testing, and will ultimately accelerate theoretical progress.