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; M. Wang, Zhou, & Zhang, 2016). As a result, many of the most influential theories in organizational psychology and organizational behaviour explicitly describe a dynamic process. Examples include Self Regulation Theory (Carver & Scheier, 1998), Conservation of Resources Theory (Hobfoll, 1989), Goal Setting Theory (Locke & Latham, 1990), the Reoccurring Phase Model of team processes (Marks, Mathieu, and Zacarro, 2001), and the Cultural Dynamics Model (Hatch, 1993). These theories describe processes that unfold within individuals, teams, or organizations over time, producing complex patterns of change with emergent properties. These dynamics can be further complicated by the existence of multiple processes unfolding at different levels of analysis and in different ways for some people or groups.

To test a dynamic theory, a statistical model must reflect the processes described by that theory (Collins, 2006). A wide range of statistical procedures have been used to analyse dynamic processes, such include multilevel regression, latent growth curve models, cross lagged panel models, and latent change 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.

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.