Many organizational phenomena are dynamic in nature, meaning that they evolve over time and are characterized by continual change (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013; Lord, Diefendorff, Schmidt, & Hall, 2010; Neal, Ballard, & Vancouver, 2017; M. Wang, Zhou, & Zhang, 2016). In recognition of this, many of the most influential theories in organizational psychology and organizational behaviour explicitly describe a dynamic process. Examples of dynamic theories include Conservation of Resources Theory (Hobfoll, 1989), the Job Demands-Resources Model (Bakker & Demerouti, 2007; Demerouti et al., 2001), Goal Setting Theory (Locke & Latham, 1990), Self Regulation Theory (Carver & Scheier, 1998), and the Cultural Dynamics Model (Hatch, 1993). These theories describe a complex set of processes that unfold within individuals, teams, or organizations over time, producing ongoing change in constructs that may be difficult to observe. Understanding these dynamics is further complicated by the fact there is often a combination of processes at play, and these processes may unfold in different ways for different people or groups.

Understanding a dynamic phenomenon requires the integration of three elements: a) a well-articulated theoretical model, b) a longitudinal design that enables the phenomenon to be observed in detail, and c) a statistical model that accurately operationalizes the theoretical model (Collins, 2006). Whilst progress has been made in articulating theories that explicitly represent processes as dynamic, and longitudinal designs are becoming more common, it is difficult to operationalize these types of theories using standard statistical models. As a result, these theories are rarely subjected to strong tests. For example, Self-Regulation Theory describes how goal striving is governed by a system of negative feedback loops, a person must dynamically reallocate resources in response to discrepancies between their goals and their current position with respect to those goals.

Testing a complex, dynamic theory such as Self-Regulation Theory is difficult using standard statistical methods. With these methods, the researcher is typically forced to distil a rich, dynamic theory into a set of simple predictions regarding the direction of relationships between variables. For example, one might hypothesise that the magnitude of the discrepancy should be positively related to the resources allocated to reduce the discrepancy, and test this prediction using linear regression. However, this hypothesis test ignores the complexity and dynamism captured by the theory. This misalignment between the theory itself (Self-Regulation Theory) and the way the theory is operationalized (a directional hypothesis tested using linear regression) means that support for the hypothesis can not necessarily be taken as evidence for the theory. Such misalignment is common in the organizational literature, and is problematic because it inhibits our ability to directly test dynamic theory.

For cumulative theoretical process to be made in this area, we need a flexible statistical framework that is capable of representing the complexity and dynamism inherent in our theories. In this paper, we demonstrate an approach that we believe is ideally suited for this purpose. This approach takes advantage of recent advances in Bayesian statistical modelling (Hoffman & Gelman, 2014; Carpenter et al., 2017), which have made it possible to implement highly customised models in a fairly straightforward manner. The flexibility of this approach allows the researcher to test relatively specific theoretical assumptions regarding dynamic theory. This ensures a close coupling between the dynamic theory and the statistical model used to test the theory, which we believe will help accelerate theoretical progress.