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. According to the theory, discrepancies between a goal and a person’s current state with respect to that goal create tension that lead the person to engage in actions that reduce the discrepancy. These actions tend to continue until the discrepancy (and therefore, the tension) is eliminated. However, environmental disturbances may produce discrepancies in other goals can introduce tension from other sources that lead the person to dynamically reallocate their resources away from their initial goal. This process continues recursively until either all discrepancies are reduced, or the tension becomes so extreme that the person abandons their goal(s).

Testing a complex, dynamic theory such as Self-Regulation Theory is difficult using standard statistical methods. With these methods, the researcher has two equally unappealing options.

The first is 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 magnitude of the discrepancy should be positively related to the resources allocated to reduce the discrepancy, and test this prediction using linear regression. This creates a misalignment between the theory itself (Self-Regulation Theory) and the statistical model used to operationalize the theory (linear regression). As a result, the statistical model will provide a poor test of the theory. The second option is to constrain the theorizing itself, moulding and shaping the theory until it conforms to a generic template that be accurately represented by standard models. For example, one might avoid Self-Regulation Theory altogether in favour of a simpler theory that is more amenable to testing by standard statistical methods. Here however, the researcher runs the risk of overlooking the complexity and dynamism of the phenomenon being investigated. Both of these options impede theoretical progress because they place hard limits on our ability to validate sophisticated 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.