There has been an increasing emphasis within organizational psychology and organizational behavior on the importance of examining how processes unfold over time (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013; Lord, Diefendorff, Schmidt, & Hall, 2010; Neal, Ballard, & Vancouver, 2017; M. Wang, Zhou, & Zhang, 2016). This emphasis is born from the observation that organizational phenomena are often dynamic in nature, meaning that they evolve over time and are characterized by continual change. Whether one is considering how performance improves with practice (e.g., Yeo & Neal, 2004), how self-regulatory processes change in response to stressors (e.g., Zhou et al., 2017), or how teams develop shared knowledge (e.g., Grand, Braun, Kuljanin, Kozlowski, & Chao, 2016), many of the questions of interest require explicit consideration of temporal dynamics.

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). We believe the field has made great strides with regard to elements a) and b). There are many examples of sophisticated theories that explicitly account for the dynamic quality of the phenomenon they were developed to explain. For example, Conservation of Resources Theory (Hobfoll, 1989) describes a dynamic process by which people pursue and protect their resources, and the downstream impacts this process has on stress. The theory predicts *gain spirals*, where acquisition of resources leads to further acquisition of resources, and *loss spirals*, where loss of resources lead to further losses in the future. Another example is Self-regulation Theory (Carver & Scheier, 1998), which describes goal striving as a dynamic process governed by a negative feedback loop. According to the theory, the goal striving process occurs within the context of a higher order goal setting process, which operates at a longer timescale and is governed by a positive feedback loop. Researchers have generally tested these theories using within-participants, longitudinal designs that allow for that allow the process being investigated to be observed at multiple points in time.

We argue that more progress is needed in developing statistical models that can accurately operationalize these theories. Capturing the dynamism inherent in theories like Conservation of Resources Theory and Self-regulation Theory in a statistical model is not trivial and requires a highly flexible approach. Such a task is prohibitively difficult using standard, off-the-shelf statistical models, which do not directly represent any specific theory,

but rather are generic tools for summarizing the relationship between variables. With these methods, the researcher has two equally unappealing options. The first is to shoehorn a rich, dynamic theory into a set of simple predictions regarding the direction of relationships between variables. This will inevitably lead to a misalignment between the theory itself and the statistical model used to operationalize the theory. As a result, the model will provide a poor test of the theory. The second option is to straightjacket the theorizing itself, moulding and shaping the theory until it conforms to a generic template that be accurately represented by standard models. 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.