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 statistical models 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. 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). Using structural equation modelling, is difficult to represent the types of phenomena inherent in dynamic theory, such as dynamic (i.e., stock or level) variables, feedback loops, or bottom-up processes. 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, such as feedback loops or bottom-up effects 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, in organizational science, computational models are typically only tested qualitatively, for example, by visually inspecting the correspondence between the output of the model and a trend reported in previous research. Models are rarely subjected to direct, quantitative tests, which require models them to be fitted to data and compared to plausible alternatives. Thus, while computational modeling has been useful for theory development in organization science, its usefulness for theory testing has yet to be realized.

In this paper, we demonstrate an approach to the development and testing of dynamic theory that capitalizes on the advantages of the two approaches described above. We demonstrate how computational modeling can facilitate the development of dynamic theory, by allowing complex process involving dynamic variables, feedback processes, and bottom-up phenomena to be instantiated in the form of a computational model. Furthermore, we demonstrate how to quantitatively test the computational model by fitting it directly to empirical data. Our approach overcomes the challenges associated with existing approaches by allowing the theory development and validation to be carried out within the same framework. The remainder of this paper is organized as follows….