Many organizational phenomena are dynamic in nature, meaning that they evolve over time \citep{Kozlowski2013,Lord2010,Neal,Wang2016a}. 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 \citep{Carver1998}, Conservation of Resources Theory \citep{Hobfoll1989}, the Reoccurring Phase Model of team processes \citep{Marks2001}, and the Cultural Dynamics Model \citep{Hatch1993}. The essential features of dynamic theories is ...."patterns, feedback loops"??

Testing dynamic theory requires the integration of three fundamental aspects of research: a) a \textit{theory} that describes the dynamic interaction between process components over time, b) a \textit{model} that formalizes the process described by the theory and allows for process components to be quantified, and c) a temporal design that allows for the \textit{measurement} of the process as it unfolds over time \citep{Collins2006}. In recent years, progress has been made in each of these areas. For example, dynamic theories such as those described above are becoming more common. Intensive longitudinal designs are becoming more widely used to measure phenomena, and a range of statistical models have been used to analyze the data collected using these designs (e.g., latent growth curve or latent change score models).

Despite these advances, there remain two broad challenges tor testing dynamic theories. First, phenomena must be observed or inferred over multiple periods of measurement with limited knowledge about the frequency or periodicity of measures that best captures the underlying process (Dormann and Griffin for cites). In addition, for any given theory, time scales and patterns of change might vary for different individuals, within different contexts, and across different levels of analysis.

Second, the analysis of measures requires statistical tools that can be difficult or cumbersome to implement. For example, statistical approaches such as latent growth curve modeling and latent change score modeling are useful for quantifying relationships between dynamic variables and examining the extent to which the model accounts for empirical data. However, using this approach, it is difficult to directly represent certain types of phenomena that are common in dynamic theory. For example, it is difficult to examine the effects of [alternative word?]dynamic variables or feedback loops, because they typically need to be modelled via simulation. As a result, there is often a misalignment between theory and model that can make the theory difficult to corroborate regardless of how much variance the model explains in the data.

In this paper, we propose that computational modelling helps to address the challenges for testing dynamic theories outlined above. Computational modeling is a method for articulating theory in the form of mathematical equations and/or computer code and evaluating the dynamic behavior of the theory by simulating the model. We position computational modeling within an overall framework linking observations, models, and theories. **Figure 1** indicates that computational models facilitate the link between theory and models, complementing statistical models which facilitate the link between models and data.

Our paper demonstrates the advantages of integrating computational models with statistical models to provide a more comprehensive way of testing dynamic theories. Computational modeling allows for a more direct mapping between theory and model, because the model is custom built to represent the processes described by the theory. Statistical models provide a more direct mapping between the model and observations because it. ...

Integration of computational and statistical models in the organizational sciences is rare. In most cases, computational models are used for theory development, rather than theory testing. The parameters of the model are often not informed by empirical data, and correspondence between the model output and the empirical data is often not directly examined. As a result, the link between the model and the empirical observations has been weaker under this approach, because it has been difficult to examine the extent to which the model is supported by the observations.

Our approach involves developing computational models of dynamic phenomena that can be applied directly to the analysis of empirical data. This approach facilitates the link between theory and model because it allows the processes described by the theory to be directly represented in the model. It facilitates the link between model and observation because it allows the process components in the model to be quantified based on the data, and for the correspondence between the model and the data to be directly examined.

In the next section, we elaborate on the challenges associated with testing dynamic theory. Following that, we introduce an example research question that we use to demonstrate our approach. The research question concerns the reciprocal relationship between effort and performance, and how the dynamics of this relationship influence goal setting over time. This question is complex because it involves non-linear relationships between various process components, a feedback loop between effort and performance, and bottom-up effects of this feedback loop on the higher-level goal setting process.

We introduce our approach in several stages. We begin by demonstrating a \textit{static} model that is used to predict levels of performance over time. We then demonstrate a \textit{dynamic} model that is used to predict the reciprocal relationship between effort and performance. Following that, we demonstrate how the dynamic model can be extended to predict the bottom-up effects of the effort-performance feedback loop on the goal setting process. We then demonstrate how this approach can be used to examine variability in this process across people, known groups (e.g., experimental conditions), or latent subgroups of participants.