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; M. Wang, Zhou, & Zhang, 2016). As a result, many of the most influential theories in organizational psychology and organizational behaviour explicitly describe a dynamic process. Examples include Self Regulation Theory (Carver & Scheier, 1998), Conservation of Resources Theory (Hobfoll, 1989), Goal Setting Theory (Locke & Latham, 1990), team process (Marks, Mathieu et al. (2001(*…[Mark – do you have a good example of a dynamic theory at the team level?]*…, and the Cultural Dynamics Model (Hatch, 1993). These theories describe processes that unfold within individuals, teams, or organizations over time, producing complex patterns of change an(and emergent properties) . These dynamics can befurther complicated by multiple processes unfolding at different levels of analysis and in different ways for some people or groups.

To test a dynamic theory, a statistical model must reflect the processes described by that theory (Collins, 2006). A wide range of statistical procedures have been developed to represent these dynamics (some review- e.g, from panel model to latent change ).

Many of these procedures have been developed within a structural equation modelling (SEM) framework that combines multivariate regression with the measurement of latent constructs. By imposing various model constraints, the general framework has been extended to encompass temporal designs such as latent growth curves and discontinuous change models. Although these models capture important dynamic processes, they are also limited in a number of ways.

First, the constraints required to model dynamics can be complex and non-intuitive.

Second, alternative models can be difficult to specify

Third,

Fourth,

Fift

For example, self-regulation theory might predict that people will allocate increasing effort to a task as a deadline approaches. This proposition might be tested using a latent growth model in an SEM framework such that individuals show a linear increase in effort over time. The SEM model might be extended to include different patterns of change (e.g., quadratic or other non-linear patterns) and variations among individuals in the specific pattern. However, self-regulation theory also proposes that a higher-level control process regulates how the person responds to difficulties encountered in goal progress. People can respond to difficulty in multiple ways, including changing strategy, extending the deadline, adjusting the goal or abandoning the task (Neal, et al., 2017). Moreover, the point at which these responses occur might also differ among individuals. The specification of the model therefore becomes increasingly complex in a standard statistical framework.

In this paper we propose a Bayesian approach to modeling dynamic processes that is more intuitive, flexible, and comprehensive than the more common extensions of the SEM framework.

we take 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.

This means that support for the hypothesis can not necessarily be taken as evidence for the theory. This is problematic because it inhibits our ability to directly test dynamic theory.

This can be difficult to do using standard statistical models. With these models, the researcher is typically forced to distil a rich, dynamic theory into a set of predictions that simplifies the direction of relationships between variables and patterns of change.

For example, using Self-Regulation Theory, one might predict that people will apply more effort in pursuit of a goal as the difficulty of the task increases, and test that hypothesis using a growth modelling. However, the theory assumes that there is a higher level control process that regulates how the person responds to difficulty. As such there is a range of different ways that people can respond to difficulty, including changing strategy, extending the deadline, adjusting the goal or abandoning the task (Neal, et al., 2017). This means that support for the hypothesis can not necessarily be taken as evidence for the theory. This is problematic because it inhibits our ability to directly test dynamic theory. *[Tim, can we try to weave something into the description of the problem in this para, so that when the reader gets to the next para, a Bayesian approach seems like a perfectly natural choice? Eg., is it something about uncertainty, prior knowledge, hierarchical structures, populations, distributions, etc? Maybe frame it as a challenge for researchers, eg the challenge for researchers is to draw inferences from longitudinal data regarding …..]*

*TB: My first thought would be make a two-pronged argument about the hierarchical structure and uncertainty. The hierarchical structure is important to touch on here given the theme of the issue is around multilevel modeling. So the argument would be about needing to account for a) process that are unfolding over time within individuals b) individual differences in these processes c) invariances at the sample level. Moreover, the constructs we’re interested in are not directly observed, so we need models need to account for uncertainty in the parameters that govern the process. The Bayesian approach provides a natural way of handling both of these issues. Mark, what do you think?*

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.