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COMMENTARY

The power of process theories to better understand and detect consequences of organizational interventions

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Organizations are complex, multilevel, dynamic systems comprised of many interacting processes (Katz & Kahn, 1966; Kozlowski & Klein, 2000). The goal of organizational interventions is to generate an intentional positive influence on the way in which one or more organizational processes unfold (Porras & Silvers, 1991). In their focal article, Watts et al. (2021) correctly point out that, through the act of intervening, unintended consequences may occur such that processes and outcomes not directly targeted by the intervention may be altered. Although Watts et al. focused exclusively on unintended negative outcomes (i.e., side effects) associated with organizational interventions, unforeseen or unintended consequences of interventions could be either negative or positive, and they are worth understanding and studying regardless of their valence. Therefore, we prefer the more neutral term "unintended consequences" to capture any influences on organizational processes or outcomes resulting from an intervention that were not directly predicted, anticipated, or intended. Unfortunately, as noted by Watts et al., the complexity of organizations ("The Challenge of Causal Attribution," p. 17), combined with the typical way in which organizational scientists develop theory ("Simplification Bias," p. 18), and conduct empirical research ("Theory Mania," p. 19) limits our current ability to understand, predict, or detect unintended consequences of interventions.

One solution, omitted by Watts et al. (2021), to better understand, predict, and detect consequences of organizational interventions is to develop more process theories combined with leveraging computational modeling. Through extending our current theories to include a more precise description of relevant organizational processes, we believe that potential consequences, intended and unintended, of interventions will become more apparent. Then, by instantiating those process theories of interventions into computational models, predictions can be made regarding when, where, why, and how interventions influence various processes. Furthermore, these computational models can be used to vet potential interventions prior to organizational implementation as well as direct research attention regarding what and when to measure to detect potential unintended consequences (Kozlowski et al., 2013).

Factor theories

Typically, theories in the organizational sciences are centered on constructs or *factors*, operationalized as variables (endogenous and exogenous) that quantify the quality, amount, or classification of something. Factor theories focus on how and why the level(s) of one factor relate to the level(s) of another factor (i.e., patterns of covariance; Kozlowski, in press; Macy & Willer, 2002; Strauss & Grand, in press), highlighted by hypotheses or propositions regarding the (linear) directionality of proposed factor-to-factor relationship(s). Consistent with the dominance of deductive research and the simplification "biases" described by Watts et al. (2021), current organizational theories also tend to focus on rather narrow sets of factors (i.e., those included in the present research), with the purposeful goal of justifying the hypotheses tested within a given research study, with little to no attention paid to the broader complex organizational context (Mathieu, 2016). These factor theories are nicely bounded and conveniently aligned with typical measurements and statistical analyses used in empirical research (Kozlowski, in press). Undoubtedly, this bounded, well-aligned, factor-oriented approach to theory development and subsequent deductive research has resulted in numerous important and robust findings, many of which have translated into effective interventions (e.g., Baldwin et al., 2009).

Although factor theories have helped to summarize, guide, and advance our understanding of relationships among constructs in the organizational sciences, their focus on how changes in one variable correlate with changes in another variable inherently downplays the *actual processes* responsible for observed relationships. We acknowledge that some may disagree that organizational theories downplay processes because process-based frameworks, like McGrath's (1964) input-process-outcome framework, have dominated organizational thinking for over 50 years. Furthermore, it is widely accepted that processes are the central mechanisms by which micro, meso, and macro inputs are converted into outcomes of interest and are seemingly discussed in many theories across a host of substantive areas. Likewise, the organizational literature is filled with models and tests of mediation whereby inputs are thought to affect outcomes via some mediator, inherently implying that a process is taking place (Maxwell & Cole, 2007). Therefore, how can most organizational theories downplay processes?

Despite clear understanding and recognition that processes represent affective, cognitive, behavioral, and social *actions* occurring over time toward the accomplishment of a goal (e.g., Katz & Kahn, 1966; Marks et al., 2001), current theoretical development and empirical testing almost always converts *actual processes* into *process factors*, which represent behavioral or perceptual *summaries* over many relevant actions regarding how frequently or how well relevant actions are performed, stripping these processes of any temporal or configural component (e.g., communication, coordination, back-up behaviors, etc.; LePine et al., 2008). In doing so, the emphasis in most theories and empirics is reduced to how levels of input factors relate to levels of *process factors* and how levels of *process factors* relate to outcomes. We believe the emphasis on factors, even *process factors*, rather than *actual processes* limits most of our current theories' applicability for predicting consequences, intended and unintended, of organizational interventions.

Lost in the translation of processes into process factors are the actual affective, cognitive, behavioral, and social actions taking place; in particular, we miss the timing, sequencing, and patterning of these actions (Macy & Willer, 2002; Strauss & Grand, in press), resulting in organizational theories that are devoid of a temporal focus (Kozlowski, 2015). Taken together, ignoring actual actions and the role of time make current theory and the resulting research particularly ill-suited to predicting and investigating the consequences of organizational interventions. After all, interventions are specifically targeted at altering affective, cognitive, behavioral, or social actions within organizations (Alliger & Janak, 1989), with the explicit recognition that these changes in action occur over time with the hopeful result of new, more efficient, and effective organizational processes. Furthermore, the types of unintended consequences discussed by Watts et al. (2021) likely take time to manifest and result from the interaction of the new patterning of actions induced by the intervention with other ongoing processes (Weick, 1979). Therefore, for theory and any resulting research to be maximally useful for understanding consequences associated with interventions, significantly more effort and attention needs to be focused on understanding processes *before*, *during*, and *after* the intervention takes place.

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Process theories for organizational interventions

In contrast to factor theories focused on explaining and justifying covariance relationships among factors, process theories focus on actors[1] and their actions, seeking to explain how and why they perform affective, cognitive, behavioral, and social actions across time (or contexts or events) toward the completion of a goal (i.e., actors' processes; Macy & Willer, 2002; Strauss & Grand, in press). In particular, the emphasis in process theory is identifying the rules or process mechanisms responsible for the observable sequence of actions (Kozlowski, in press). Therefore, the goal underlying a process theory is to explain why each actor in the focal system performs a particular action at a particular time in a particular way.

Admittedly, it can be very challenging to conceptually disentangle factor theories from process theories. To demonstrate the difference in theorizing, especially with respect to organizational interventions, consider the example of information sharing in distributed-expertise teams. A common finding is that when teams are composed of several subject matter experts, those experts tend to insufficiently share their unique information (i.e., pass on their expertise), resulting in suboptimal decisions and overall process loss (Stasser & Titus, 1985). Indeed, meta-analytic evidence indicates that teams share two standard deviations more common information than unique (diagnostic) information (Lu et al., 2012) and that teams which are more willing and/or able to share information make better decisions and overall perform better (e.g., Mesmer-Magnus & DeChurch, 2009). The commonly prescribed information-sharing intervention based on these factor-oriented conclusions is to encourage more discussion in teams with diverse expertise with the hope that more communication will contribute to more sharing of novel information and ideas, ultimately resulting in better decisions and performance.

Alternatively, a process theory of information sharing in distributed expertise teams seeks to represent which, when, how, and why individuals engage in information-sharing activities while working in a team, as it is through these interactions that unique patterns of communication and knowledge emerge within a team that ultimately determine its decision making and performance (Grand et al., 2016). Having such a process theory subsequently facilitates the identification of interventions that target the sequencing and patterning of *who shares which type of information when* and how those actions can lead to differences in information sharing within the team and improved decisions/performance. In fact, Grand et al., (2016) found that the sequencing of information sharing, not the quantity of shared information, was the most diagnostic of knowledge emergence and decision making. To summarize, a factor theory of information sharing is capable of proposing interventions focused on affecting how much or how often information is shared within the team (e.g., more information sharing should result in better decisions/performance). In contrast, an intervention from a process theory of information sharing targets the patterns of information exchange among members within the team (i.e., who, how, which, when, and why information is exchanged should result in better decisions/performance)—that is, influencing the actions/processes that are *directly responsible* for the desired outcomes.

This example highlights the differences and, importantly, benefits of process theory for understanding and implementing organizational interventions and the consequences that emerge from those interventions. Although factor theories nicely align with our typical measurement and statistical modeling procedures (Kozlowski, in press), process theories nicely align with the actual affective, cognitive, behavioral, and social actions that actors perform, providing a gateway to the processes targeted by interventions (Macy & Willer, 2002; Strauss & Grand, in press). This alignment between process theory and action has three primary benefits with respect to organizational interventions and their consequences. First, because process theories focus on actions, we can more easily translate them into interventions, targeting specific actions at specific times during relevant performance episodes (e.g., Grand et al., 2016). This targeting improves the precision

[1]Actors may represent any units of interest (individuals, teams, systems, organizations, etc.) performing the focal actions comprising the theory.

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and efficiency with which we may implement interventions. Second, an increase in the precision of interventions provided by process theories can more easily reveal the number and severity of potential unintended consequences. All the unintended consequences resulting from organizational interventions described by Watts et al. (2021) were unintended because they lacked precision and specificity with respect to how, why, when, and which processes/actions should be altered at critical times. They were high-level interventions that were directed at altering the overall levels of factors, like in the factor-oriented information sharing example. However, by targeting specific actions at specific times during relevant performance episodes, we are better equipped to understand how an intervention may alter some tangential process that might result in an unintended consequence. Finally, the act of theorizing which processes are involved in the focal phenomena, as well as how an intervention should alter those processes will make researchers more aware of which types of processes could be influenced by their interventions. This provides an opportunity for the measurement and study of not only focal processes but related ones as well. Ultimately, this may result in detecting and mitigating, if not eliminating, undesired consequences of interventions within organizations.

Computational modeling for predicting and detecting consequences of interventions

One final benefit of process theorizing for understanding and implementing organizational interventions is its alignment with computational modeling.[2] Computational models attempt to use logical rules or mathematical formulas to explain how processes dynamically relate to one another to ultimately generate actions that mirror human behavior (Epstein, 1999; Kozlowski et al., 2013). These rules or formulas are typically instantiated into computer code to create computer simulations that allow researchers to "see" the implications of their theory by examining patterns that are generated in simulated data. Given that process theories attempt to discover the process mechanisms responsible for the affective, cognitive, behavioral, and social actions of actors, those mechanisms become the foundation for specifying the rules/formulas necessary to build a computational model and create a computational simulation. Notably, Watts et al. (2021) suggest that one solution to better anticipate unintended consequences of interventions is to engage in *mental* simulation and forecasting. However, they also recognize that the contexts and environments in which our interventions and phenomena of interest exist reside in *complex social systems*—which, by definition, means that attempting to mentally predict the trajectories or likelihoods of particular consequences given knowledge of initial inputs/conditions is exceedingly difficult (if not impossible; Epstein, 1999). Furthermore, the cognitive faculties of human beings are not well suited to mentally simulating or making accurate predictions when phenomena involve dynamic processes over time (e.g., Cronin et al., 2009; Farrell & Lewandowsky, 2010).

Consequently, computer simulations of computational models developed from process theories provide an immensely valuable tool for understanding the influence of interventions for several reasons stemming from the way in which simulations can be composed and the resulting data they generate. First, the proposed intervention can be modeled with respect to the theoretical processes it is designed to influence to ensure that the overall theory is logically consistent and works as anticipated (Naylor & Finger, 1967), potentially saving time and resources prior to executing the intervention in the field. Second, it is also possible to test the intervention under conditions that are difficult to sample in organizations due to low power or limited accessibility, such as across many different types of individuals, teams, or cultures, or at different points in time (Kozlowski et al., 2013). This offers researchers the opportunity to determine the ideal conditions under which to perform their interventions, potentially maximizing their effectiveness

[2]We use the term computational modeling in the general sense to describe a methodology that takes computational theory, instantiates it into computer code, and runs computational simulations.

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while minimizing unintended consequences. Likewise, it allows the effectiveness of the intervention to be evaluated on all different samples, even those to which the organization does not immediately have access, which can help determine the robustness of a given intervention or identify potential moderators of success. Third, the primary intervention could be compared with alternative interventions (including no intervention) to estimate the differential effectiveness of possible courses of action. This allows the effect of inaction to be evaluated along with testing multiple options without burdening employees or spending valuable organizational resources.

Using the data that are generated through the types of simulations referenced above allows both the short- and long-term consequences of an organizational intervention to be detected (Harrison et al., 2007; for one example, see Samuelson et al., 2019). Although it is often extremely difficult to collect data over many time periods within organizations, limiting the possibility of traditional empirical data collections to evaluate the long-term consequences of interventions (as noted by Watts et al., 2021), computational simulations can easily model hundreds or even thousands of time points. This elongated temporal lens allows difficult-to-foresee (i.e., unintended) outcomes to be anticipated prior to implementing an intervention within an organization (Sargent, 2013), minimizing or eliminating unintended consequences. Last, the ability to examine theoretical processes of interest over both short and long time horizons within the simulated data allows researchers to identify critical instances for measurement. One problem with simply using inductive research to understand unintended consequences of interventions, as recommended by Watts et al. (2021), is that, devoid of theory, it will be difficult to know what to measure and when so that these consequences can be seen (i.e., one of the major problems we have now in our empirical databases). Given that capturing phenomena over time within organizations is challenging due to practical constraints, allowing computational models to target which processes should be measured when saves critical resources and enables more efficient and effective testing of how well organizational interventions are performing, as well as whether they are having any unintended consequences.

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