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COMMENTARY

Computational process theorizing for defining, refining, and differentiating constructs

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Constructs are foundational for organizational science (OS). They are the building blocks for the dominant form of theorizing in OS (Kozlowski, 2022; Kozlowski et al., 2026; Kuljanin et al., 2024), serve as the focus of psychometrics and measurement (Cronbach & Meehl, 1955; Shadish et al., 2002), define the variables included in statistical analyses (Cohen et al., 2003), and serve as the basis for organizational interventions and policy recommendations (Antonakis, 2017). As a result, our theory, measurement, analyses, and recommendations are only as useful as the constructs that comprise them. Bowling et al. (2026) correctly point out that construct proliferation threatens to undermine scientific advancement by reducing "the quality, validity, and applicability of the predictions and explanations that our field offers" (p. 15). Therefore, it is critical that construct proliferation is identified, redundant constructs are pruned, and parallel research streams are integrated.

However, we also contend that construct proliferation is symptomatic of a more fundamental issue concerning how predictions, explanations, and theory are developed in OS—namely, the (over)reliance on constructs as the means for understanding individuals, teams, and organizations. At its core, OS is focused on advancing knowledge that provides insight into how phenomena relevant to the workplace "happen" (i.e., *processes* and their *generative mechanisms*) as well how such occurrences could be influenced in desirable ways (Kozlowski, 2022; Kozlowski et al., 2026; Kuljanin et al., 2024). Unfortunately, research and theorizing that focuses solely on constructs and their interrelationships are incapable of revealing knowledge of the causal processes and mechanisms underlying a phenomenon (Newell, 1973; Shadish et al., 2002). Indeed, constructs and the relationships among them are consequences of mechanisms and processes unfolding and interacting over time (Kozlowski et al., 2026; Simon, 1992). Thus, although the proliferation of constructs is an issue worthy of attention, we contend that this concern could be more fruitfully addressed by instead embracing new ways of thinking about the problems and accounts we pursue that explicitly acknowledges the generative mechanisms and processes that give rise to constructs and their interrelationships.

To this end, we propose that one potential solution for reducing construct proliferation and improving organizational theories is utilizing *computational process theorizing* to help guide construct definition, operationalization, and, ultimately, differentiation. Computational process theories apply formal logic, math, and computer simulation to explain how organizational phenomena emerge, change, and/or evolve over time as a function of actions enacted by actors. Computational process theorizing requires a researcher to precisely specify the action/event

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sequences (i.e., processes) enacted by actors that convert their inputs into their outputs (Grand et al., 2025; Kuljanin et al., 2024). In terms of constructs, their functional role must be articulated by identifying exactly what processes, tendencies, and/or perceptions comprise each relevant construct in the model and translating them from narrative descriptions into precise computational representations. Then, simulated data can determine the implications of the proposed theory (Braun et al., 2022; Kozlowski et al., 2013, 2016). In addition to facilitating more actionable and precise knowledge, we believe computational process theorizing can aid with identifying potentially redundant constructs and help refine construct definitions/measures, which ultimately results in better theoretical integration across research domains.

Computational process theorizing reduces construct proliferation

Most explanatory accounts in organizational science adhere to *narrative construct theorizing* (Kuljanin et al., 2024). Such accounts use words (i.e., narratives) to describe the rationale behind expected (typically linear) relationships among constructs (Macy & Willer, 2002; Strauss & Grand, 2022). By contrast, computational process theorizing uses formal logic, math, and computer simulation (i.e., computational modeling[1]) to describe the underlying generative mechanisms responsible for observed affective, behavioral, cognitive, and/or social (ABCS) action/event sequences (Grand et al., 2025; Kuljanin et al., 2024). Initial thinking in the research literature described narrative and process theories as being in opposition to one another (Mohr, 1982). More recently, however, Kozlowski et al., (2026) proposed a more integrative account that explains how these two types of theorizing are related but focused on different *layers of theoretical explanation*. Construct theorizing emphasizes the relationships between constructs, using implicit processes as the explanation for how/why constructs are related to one another. In contrast, process theorizing emphasizes the significance of observed ABCS action/event sequences, using explicit mechanisms as the explanation for how/why processes unfold over time, and ultimately, produce construct relationships. Because construct theories rely on process explanations, the ABCS processes at the forefront of process theorizing can be used to define or create the constructs and construct relations that are typically theorized and empirically examined in the organizational literature (Kozlowski et al., 2026). We next discuss two primary ways computational process theorizing may serve to reduce construct proliferation by ensuring constructs are conceptually and empirically distinct (Bowling et al., 2026).

Functional role of constructs

Computational process theorizing requires scientists to specify exactly how constructs functionally affect processes and result from processes. For example, take a common individual difference construct such as extraversion (e.g., Barrick & Mount, 1991). To develop a computational process theory, researchers must specify how they believe extraversion impacts ABCS actions. That specification requires thinking about the functional representation and role of each construct. Should extraversion be represented by a single, time-invariant number for each actor (e.g., a value from 1 to 5 as on a Likert scale)? Or should extraversion be represented as a density distribution around a mean value representing the trait level and the variance representing state-level idiosyncratic variations across time (e.g., Fleeson, 2007)? If state-level variations around the trait are to be included, should those variations be random, or should they be dependent on other

[1]A review of computational modeling is beyond the scope of this paper. However, there are a variety of resources for basic background (e.g., Ilgen & Hulin, 2000; Miller & Page, 2007; Prietula et al., 1998; Vancouver et al., 2023; Weinhardt & Vancouver, 2012). For more specificity, we recommend Kozlowski et al. (2013, 2016) for a detailed account of integrating computational modeling into organizational research, Kozlowski et al. (2026) for the advantages of computational process theorizing for theory building, Kuljanin et al. (2024) for how to create computational process theories, and Grand et al. (2025) for how to build computational models using R, focusing on translating organizational theories into actionable computer code.

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processes in the theory such as actions of other actors, features of the environment (e.g., strong situations; Mischel, 1973), or anything else? How researchers answer these kinds of questions clarifies exactly how constructs manifest in the actions of actors and how any specific construct interacts with and influences other inputs, processes, or outcomes. This process of explicitly defining the functional role of each construct helps theorists identify sources of theoretical overlap and distinctiveness.

As another example from the research literature, Bowling et al. (2026) noted how transformational, ethical, and servant leadership have nearly identical measurement related to ethical tendencies. Hence, a relevant question becomes: Are those forms of leadership distinct or redundant? Leadership, as a research area, is heavily criticized for its disparate nature and ever-expanding list of leadership styles (Bass, 1990; Dinh et al., 2014). A review of the leadership literature indicates that many supposedly distinct leadership styles stem from the same foundational ABCS processes (Banks et al., 2018). Precisely instantiating each style within a unified computational process theory would allow researchers to specify how each style is differentially related to input constructs, how each style behaves differently in terms of the ABCS processes undertaken, and how each style is differentially related to outcomes. Overall, the functional specification of constructs in computational process theories allow potential redundancies in inputs, processes, or outcomes to become apparent, eliminating proliferation by ensuring each relevant construct remains conceptually distinct. Indeed, computational process theorizing can also prevent organizational scientists from falling victim to the jingle or jangle fallacies[2] and help integrate parallel and related research domains (Hanfstingl et al., 2025).

Short- and long-term implications of construct differences

Computational process theorizing ensures constructs are empirically distinct by distinguishing short- and long-term implications of construct differences on organizational or societal outcomes via simulations (Harrison et al., 2007; for one example, see Samuelson et al., 2019). A primary practical recommendation offered by Bowling et al. (2026) is for practitioners to examine the uniqueness of the insights, interventions, and policy decisions that would result from different constructs; essentially, they encourage only adopting a new construct if it results in novel and distinct organizational or societal outcomes. To do so, organizational scientists might go one of two ways. On the one hand, researchers and practitioners might conduct considerable empirical work to understand the implications of each construct. Yet, it may prove difficult, costly, and time intensive to collect large amounts of empirical data, which could result in years of work only to identify redundant (proliferated) constructs. On the other hand, research and practitioners might *mentally* extrapolate short- and long-term outcomes of different constructs. Relative to the first approach, mental extrapolation will undoubtedly prove less costly and time intensive. Yet, individuals consistently fail to mentally extrapolate consequences of even simple ongoing processes (Cronin et al., 2009; Epstein, 1999). Fortunately, we may simulate computational process theories, which permits researchers and practitioners to examine differential implications of multiple constructs at differing time scales without significant physical, temporal, or mental costs (Braun et al., 2022).

Simulations of a computational process theory highlight its implications. In other words, under the specified computational process theory, we can use simulations to highlight the implications of each construct with respect to its effects on how processes unfold and examine how construct relationships emerge from ongoing processes. Therefore, simulations allow researchers and practitioners a means of evaluating the short- and long-term implications of their theories (Harrison et al., 2007), enabling difficult-to-foresee outcomes to be discovered and anticipated

[2]The jingle fallacy occurs when two or more different phenomena are labeled with the same name (Thorndike, 1904), whereas the jangle fallacy occurs when the same phenomenon is labeled with two or more different names (Kelley, 1927).

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(Sargent, 2013). Importantly, simulations are not subject to the same practical limitations as traditional experimental or observational approaches (Braun et al., 2022). For example, it is possible to simulate difficult to reach populations, explore low base-rate or "dark corners" of the theoretical space, and generate data on many more units than would be empirically possible (Kozlowski et al., 2013, 2016). Simulations also provide insight into the temporal scale of the phenomena under investigation, directing research attention to what constructs should be measured when (Braun et al., 2022). This directed empirical attention can minimize unnecessary costs associated with experimental or observational data collection and allow construct proliferation to be more efficiently evaluated. Taken together, simulations allow organizational scientists a means of testing the distinctiveness of constructs under a wide variety of conditions, even those that are empirically intractable, providing initial evidence as to the potential redundancy of constructs. Then, researchers and practitioners can collect targeted empirical evidence to ultimately determine the presence or absence of construct proliferation.

Computational process theorizing facilitates construct refinement

Besides construct proliferation, Bowling et al. (2026) discuss construct refinement. Construct refinement consists of clarifying the boundaries and improving the measurement of a construct with the goal of ensuring a meaningfully distinct construct exists. The process of construct refinement serves to detect and reduce construct contamination by clarifying the definition, purpose, relationships, and measures of each individual construct. Computational process theorizing helps researchers refine their constructs due to the requirement of specifying each aspect of a construct or process in such a way that a computer can understand and execute (Grand et al., 2025). The challenges associated with construct instantiation into computer code can often result in identifying areas in need of construct refinement.

It can be difficult to conceptualize how the construct refinement process works in the abstract. As such, consider the example of team knowledge emergence presented in Grand et al. (2016). Team knowledge is typically defined as the overall quality and/or quantity of knowledge collectively held by members of a team (e.g., Fiore et al., 2010). Under such definitions, teams with higher quality or quantity knowledge generally make better decisions than teams with lower quality or quantity knowledge (e.g., DeChurch & Mesmer-Magnus, 2010), which implies that simply increasing the overall level of knowledge quality/quantity should serve as an effective intervention to improve team decision-making. The commonly identified mechanism for improving knowledge quality/quantity is information sharing, such that teams that share more information tend to have higher levels of collective knowledge (e.g., Mesmer-Magnus & DeChurch, 2009).

In creating a computational process theory of knowledge emergence within teams, Grand et al. (2016) found that solely examining the overall amount of knowledge quality or quantity collectively held at the team level was insufficient to explain the observed dynamics. Rather, team knowledge as a construct needed to be refined and further specified to better differentiate teams and explain results. To this end, Kozlowski and Chao (2012) and later Grand et al. (2016) separated overall team knowledge into multiple constructs designed to collectively capture team knowledge emergence as a process. Specifically, they defined individually held knowledge as knowledge accurately known by only one member of the team, partially shared knowledge as knowledge accurately known and acknowledged by more than one member of the team but less than the entire team, and fully shared knowledge as knowledge accurately known and acknowledged by all team members. Teams with the same overall amount of knowledge could drastically differ with respect to the distribution of knowledge held across team members, subgroups, and the team, with differing configurations resulting in different outcomes. Through these three team knowledge constructs, the dynamics of knowledge emergence could be better

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observed and understood than would have been possible with the broad overall level of team knowledge commonly conceptualized and measured in the organizational literature.

Importantly, capturing the nuances of emerged knowledge led to insights regarding other constructs in the model. As previously noted, the common mechanism thought responsible for higher quality/quantity knowledge in the team was information sharing with the insight that teams that share more information tend to have more collective knowledge (e.g., Mesmer-Magnus & DeChurch, 2009). However, Grand et al. (2016) discovered that simply examining amount of information shared was insufficient to explain knowledge differences within teams. It also mattered *how* that knowledge was shared. Unique patterns of sharing consistently resulted in distinct knowledge emergence outcomes for teams, with teams whose members shared approximately equally over time achieving the best outcomes. In other words, sharing more was helpful, but sharing more with a particular pattern (i.e., evenly across members over time) was the optimal practice. Grand et al. (2016) used this insight from the computational process theory to design an empirical experiment to test whether knowledge sharing patterns truly mattered and found that teams that shared in an even manner consistently outperformed teams that shared using other patterns, holding the total amount of shared knowledge constant. The team knowledge emergence example showcases the potential for computational process theorizing to help identify and define distinct constructs within a given research domain.

Creating computational process theories to reduce construct proliferation

Identifying and reducing construct proliferation via computational process theorizing requires researchers to first create a construct theory of their phenomena of interest, including all highly related (potentially proliferated) constructs. That construct theory must then be translated into a computational process theory. A complete detailing of the process of translating a narrative construct theory into a computational process theory is beyond the scope of this paper. Doing so requires two important steps: first, converting a construct theory into a process theory, and second, instantiating that process theory into computer code so it can be simulated and the full implications understood. Kuljanin et al. (2024) explains this two-step process in detail and provides the requisite components of a computational process theory. In addition, Kozlowski et al. (2026) presents an example of converting a construct theory into a process theory, which may be used as a guide for researchers. Finally, Grand et al. (2025) details the basic skills necessary for instantiating a process theory into computer code to generate simulated data.

Once a computational process theory of the phenomena under investigation is constructed, it can be used to explore theoretical distinctions and redundancies regarding how each construct is functionally represented and interacts with other constructs, processes, and mechanisms in the model. Virtual experiments can then be conducted by systematically manipulating each relevant construct or process in the model (Kozlowski et al., 2016; see Grand et al., 2016 for an example) and using the resulting simulations as initial evidence of construct redundancy or distinctiveness. Last, the simulations should be used to direct targeted experimental and/or observational research to further empirically evaluate construct proliferation and enhance theoretical integration of parallel and related research streams (Braun et al., 2022).

Conclusion

In conclusion, although we agree that construct proliferation is a noteworthy problem in OS, we suggest that a more impactful solution is to build stronger theory that is *not* fundamentally founded on constructs. This note is particularly important for OS, which endeavors to understand complex, multilevel, process phenomena in organizational systems (Katz & Kahn, 1966; Kozlowski & Klein, 2000). We assert that building theory via computational process theorizing has

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multiple benefits including (a) specification of the underlying generative mechanisms that drive ABCS process sequences, (b) representation of those action/event sequences in simulations, (c) extrapolation of those process actions into construct representations at multiple system levels and over time, and (d) identification of targeted experimental and/or observational research for studying constructs and construct relationships. By building better theory, and thereby developing a better understanding of the functional role of construct phenomena, we can better evaluate the unique theoretical and empirical value of different construct conceptualizations.

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