Computational Modeling in Organizational Diversity and Inclusion

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Our ability to reach unity in diversity will be the beauty and the test of our civilization.
– Mahatma Gandhi

Diversity, inclusion, and equity have been—and remain—among the most energizing, widespread, and challenging social issues faced by humans. The exclusion of, preference for, and distinctions among individuals based on their physical features, group memberships, and/or value and belief systems are intimately interwoven into the legal, moral, and cultural fabric of society. These matters continue to carry significance for the workforce, organizations, and their members. Indeed, greater organizational diversity has been linked to improved organizational performance and employee satisfaction, among other desirable outcomes (Adler, 2001; Catalyst, 2004; Fields & Blum, 1997). Consequently, topics such as understanding and overcoming implicit bias in workplace interactions, integrating and leveraging the benefits of socio-culturally diverse groups, and adapting organizational practices and policies to ensure equal and equitable opportunities for all employees continue to be among the most important workforce topics among organizational researchers and practitioners (SIOP, n.d.).

Although diversity and inclusion have been of interest in I/O psychology for nearly a century, recent reviews of this literature claim that progress in this domain has begun to stagnate. For example, Colella, Hebl, and King (2017) note that while research has helped to establish antecedents and negative consequences of employment discrimination, it has been less successful at providing “a clear direction for its resolution” (p. 507). Furthermore, foundational theory from the organizational sciences on these topics has remained static and has largely ignored the “black box” regarding how, why, and when exclusionary social contexts and individual behaviors emerge or the advantages of diversity are likely to be realized (e.g., Colella et al., 2017). Another factor contributing to this perceived stagnation concerns the unique methodological challenges faced by diversity and inclusion researchers that make critically examining explanatory accounts and interventions difficult using conventional approaches. Recruiting samples from minority populations (members of which may be difficult to reach, have concealable identities, and/or be wary due to past mistreatments of their cultural groups by the research community), overcoming social desirability effects around sensitive topics, collecting data across multiple organizational levels, and examining how effects unfold over long stretches of time have all been noted as significant impediments to advancing diversity and inclusion scholarship (Roberson, Ryan, & Ragins, 2017).

In light of these accounts, the central purpose of this chapter is to describe the application of computational modeling and the utilities it can afford to research and practice on organizational diversity, inclusion, and equity. Computational modeling techniques are not new in the diversity sciences. Indeed, some of the most well-known and influential computational models in all the social sciences concern matters relevant to diversity researchers (e.g., Schelling's, 1971, model of residential racial segregation; Axelrod's, 1997, model of culture dissemination). However, the use of computational models for clarifying and testing theory, examining "what ifs" to inspire and probe the plausibility of new ideas, and extrapolating the impact of interventions is still largely a fringe practice that has gained little traction in either the organizational or mainstream diversity sciences literature.

In this chapter, we aim to provide an accessible point of departure for researchers and practitioners interested in learning about and pursuing computational modeling methods for topics germane to the diversity sciences. Our chapter is divided into three main sections. We first briefly make a case for the value of computational modeling to diversity and inclusion researchers and practitioners. To accomplish this goal, we highlight what we see as the "big questions" that orient research and practice in diversity science, the major obstacles to addressing these questions, and the utility of computational modeling techniques for those challenges. In the second section of our chapter, we articulate a critical precondition for those interested in integrating computational modeling into diversity science—how to *think* in computational modeling terms. We root this discussion in the substantive content of interest to diversity and inclusion investigators by introducing, organizing, and discussing prominent concepts from the diversity sciences into a framework that we believe facilitates computational model "thinking."

The final section of our chapter examines how computational modeling has been applied to explore topics relevant to diversity and inclusion in the organizational sciences and adjacent literatures. Based on our review, we identify the most common computational modeling approaches previously used and the types of questions in diversity science for which those approaches are particularly well-suited. We then select and review in greater detail three exemplar models by discussing how the model operates, its key assumptions, and the unique insights and predictions it advances. The three models chosen for this purpose were purposefully selected to illustrate (a) how different types of modeling approaches can be meaningfully applied and (b) the breadth and scope of topics to which computational models can be directed to advance diversity and inclusion research/practice. Lastly, we conclude by considering ways in which these exemplar models could be further developed to encourage the continued pursuit of computational modeling by diversity and inclusion scholars.

Why Computational Modeling for Organizational Diversity and Inclusion Research?

The conceptual and empirical foci of diversity scientists encompass a broad array of topics that range across the individual, group, and organizational/sociocultural levels of analysis. This work also runs the gamut from "basic" and highly generalized (e.g., theoretical underpinnings of stereotypes) to "applied" and more narrowly tailored (e.g., validating interventions targeting conscious and unconscious bias). At the risk of oversimplifying such a robust and vibrant area of research, we propose three questions that broadly characterize the impetus of theoretical and empirical work on diversity and inclusion in the organizational and social sciences:

1. What are the psychological and social *processes* underlying the formation of stereotypes and stigmas, the development of prejudicial attitudes, the enactment of discriminatory behaviors, and the occurrence of stratification/segregation?

2. What are the *consequences* of stereotypes/stigmas, prejudice, discrimination, and stratification/segregation for targets, non-targets, and organizations?
3. How can the impact of stereotypes/stigmas, prejudice, discrimination, and stratification/segregation be *mitigated or overcome*?

Although the research conducted within and across these thrusts exhibits considerable variability, we believe there are three "grand challenges" for diversity researchers that crosscut these foci (cf., Roberson, 2012). First, there are *multiple ways to conceptualize and operationalize the fundamental concepts underlying the phenomena of interest*. For example, some diversity research and theories emphasize the type or visibility of attributes that distinguish individuals (e.g., Harrison, Price, & Bell, 1998; Pelled, 1996), whereas others stress the significance of how those attributes are distributed across individuals (e.g., Harrison & Klein, 2007; Lau & Murnighan, 1998). Second, the phenomena of interest to diversity and inclusion researchers are believed to be *a function of multiple mechanisms that operate simultaneously and at different levels of analysis*. For example, explanations for the under-representation of women in leadership positions have cited several possible contributors, including gender role stereotyping, work-family pressures, ambivalent sexism, tokenism, and the nature of mentoring/developmental opportunities (e.g., Eagly & Carli, 2007; Glicke & Fiske, 2001; King, Hebl, George, & Matusik, 2009). Lastly, the phenomena of interest to diversity scientists are *dynamic, emergent, and unfold as patterns over time*. Stereotypes and stigmas are constructed, maintained, and change as individuals' beliefs and experiences evolve (Colella, McKay, Daniels, & Signal, 2012); social and demographic groups can become segregated and stratified through repeated enactment and enforcement of behaviors, practices, and policies (Schelling, 1971); and the efficacy of interventions aimed at reducing discriminatory actions are reflected in trends, trajectories, and changes in indicators of inclusion over time (Roberson, 2012).

These "grand challenges" are formidable. However, they also highlight where and how computational modeling and simulation techniques can provide value to diversity science. With respect to the first challenge, computational models permit one to incorporate, integrate, and examine the implications of different conceptualizations and operationalizations of diversity constructs independently or simultaneously. For example, a computational model can be constructed that allows one to simultaneously explore how differences in the level or type of attributes *within* individuals interact with differences in the distribution of those attributes *across* individuals. In relation to the second challenge, computational models are uniquely suited for representing and exploring the effects of multiple and simultaneous processes, including those that operate at different levels of analysis or time scales. Thus, one can construct a computational model in which social categorization processes at the individual-level facilitate segregation in an organization that is subsequently exacerbated by structural differences in the opportunities and resources afforded to particular groups. Finally, computational modeling and simulation can help to address the third challenge by permitting researchers to examine and extrapolate how, which, and under what conditions key variables and outcomes might change or unfold as the dynamics of a system play out over time across individual, group, and organizational levels. For example, "what if" scenarios can be constructed that allow one to emulate the impact of introducing different diversity and inclusion initiatives into an organizational system (e.g., changes designed to reduce biases in selection practices versus performance management systems) that can provide potential insights into bottlenecks, time lags, and critical points of leverage for improving the experiences of historically disadvantaged groups. In sum, the potential for computational modeling and simulation techniques to address some of the most significant challenges in diversity and inclusion research is substantial.

Thinking Computationally in Organizational Diversity and Inclusion Research

We suspect that most diversity and inclusion scholars perceive the primary barrier to engaging in computational modeling to be the "quantitative" and programming skills needed to code and create a model. These proficiencies are undoubtedly important. However, we believe the far more critical development is the need to first (re)train oneself on how to "think" computationally. Computational thinking requires moving beyond describing and/or accounting for patterns of covariation between constructs (e.g., “box-and-arrow” path models, mediation/moderation) to *elaborating the processes believed to generate an observed phenomenon*. There are several excellent general discussions on this topic (e.g., Davis, Eisenhardt, & Bingham, 2007; Harrison, Lin, Carroll, & Carley, 2007; Macy & Willer, 2002; Vancouver & Weinhardt, 2012), and other chapters in this volume guide this process in the context of particular modeling approaches (REFERENCES TO OTHER RELEVANT CHAPTERS IN BOOK). Here, we wish to situate this conversation more concretely for the diversity and inclusion investigator by introducing a set of terminology we have found useful for prompting “computational thinking” and then using it to organize several fundamental topics commonly discussed in the diversity sciences (see Table 1 for summary).

In our view, all computational models require one to consider three elements—(1) *core concepts,* (2) *process mechanisms,* and (3) *emergent/dynamic outcomes.* The core concepts of a computational model typically entail the fundamental properties, states, variables, attributes, etc. that will belong to and/or describe the entities and environment under investigation. In diversity and inclusion research, this will most critically involve the conceptualization and meaning of “diversity” in one’s topic of inquiry (cf., Harrison & Klein, 2007). As shown in Table 1, diversity researchers have considered several perspectives from which “differences between people that may lead them to perceive that another person is similar to, or different from, the self” (Roberson, 2012, p. 1012) could be defined. Though all of these definitions entail something about differences in the type, level, or distribution of attributes in a group of individuals, different conceptualizations draw attention to varying levels of granularity and operationalizations that carry implications for modeling a given phenomenon. For example, distinguishing between surface- and deep-level attributes may be relevant for modeling how individuals organize into social groups based on their shared features. However, incorporating differences in the observability of individuals’ characteristics may not be a core concept in a model examining how market competition can contribute to wage discrimination or preferential hiring across demographic groups.

The process mechanisms of a computational model describe how, why, and under what circumstances the core concepts in a model function, interact, and change over time. The process mechanisms are the “engine” of a computational model, and typically describe the series of emotional, cognitive, and/or behavioral actions that translate inputs into outputs and propel a system from its current state (i.e., how things look at time = t) to a new state (i.e., how things look at time = t + 1). The diversity and inclusion literature is again replete with potential process mechanisms, including social identification, social categorization, and social competition (see Table 1 for several examples). However, direct accounts and demonstrations of exactly *how* these mechanisms are carried out or operate in conjuction to influence outcomes relevant to diversity and inclusion phenomena is often lacking (e.g., What are the differences between social comparison and social identification processes? How do the environments, individuals, collectives, etc. change in response to different mechanisms? What conditions influence whether a particular mechanism is likely to be employed versus another?). Striving to precisely represent and work through the details of such process mechanisms is often the distinguishing feature and major contribution of a computational model. Consequently, this focus is where diversity and inclusion scholars interested in modeling should expect to direct a significant portion of their attention.

Lastly, the emergent/dynamic outcomes of a computational model capture the patterns, properties, trajectories, and configuration of variables that come into being as a result of enacting a model’s process mechanisms over time. In some respects, these can be thought of as the “dependent variable” in a computational model—with the important caveat that such outcomes are nearly always emergent/dynamic and tend to exhibit recurrent effects that simultaneously serve as inputs into how a process plays out over time. Given this definition, some diversity and inclusion researchers may be surprised (or even disagree) with our characterization of stereotypes/stigma, prejudice, discrimination, and segregation/stratification as emergent/dynamic outcomes in Table 1, as these are more commonly treated as causal/feed-forward factors in many empirical studies and theories. Indeed, these phenomena can serve this role in computational models as well. However, we purposefully elected to treat these topics as emergent/dynamic outcomes to emphasize that they are inherently the result of some previous and/or ongoing set of processes and therefore can exhibit dynamic properties. Stereotypes and stigmas are acquired, transmitted, and reinforced through intrapersonal experiences and interpersonal interactions (Cuddy, Fiske, & Glick, 2008); prejudicial attitudes are formulated and maintained through cognitive appraisals and evaluations (Allport, 1954); engaging in discriminatory behavior is a function of felt emotions and intentions (Talaska, Fiske, & Chaiken, 2008); and groups can become segregated and stratified as a result of perceptions, policies, and practices (Schelling, 1971). The extent to which a diversity and inclusion researcher is explicitly interested in treating these elements as more endogenous/dynamic versus exogenous/fixed in a computational model will likely depend on a model's focus and purpose. Nevertheless, we believe the recognition of these phenomena as more than fixed and "feed-forward" factors is useful for stimulating future modeling efforts within this domain.

Computational Models Related to Organizational Diversity and Inclusion

Having articulated the value proposition of computational modeling as well as some foundational concepts for thinking computationally in organizational diversity and inclusion research, the remainder of our chapter illustrates several published computational models relevant to diversity and inclusion science. Rather than conduct a systematic review, our primary goal was to collect a sample of published models to serve as a resource for those interested in learning more about how computational modeling has been applied to examine diversity-related topics. Given that computational modeling has not been widely adopted in the mainstream organizational psychology literature, we broadened our search to include published models from general psychology, sociology, economics, organizational behavior, and computational and mathematical outlets. Overall, our review revealed many excellent use cases of computational modeling applied to diversity and inclusion topics. Nevertheless, there are also myriad untapped opportunities to integrate modeling methodologies in this research domain.

Given our goal of drawing attention to the modeling methodology rather than the substantive foci of the research per se, we organize the following examination of the models according to the *type* of modeling approach utilized (see Harrison et al., 2007, for a list of computational modeling techniques). There is seldom a single "right" or best way to model a phenomenon, and different modeling techniques tend to draw attention to different aspects, perspectives, and inferences of a problem (Page, 2018). Nevertheless, our review revealed that existing computational models of diversity and inclusion have primarily relied on two distinct modeling approaches: *neural network/connectionist models* and *agent-based models*.[1] In the sections below, we briefly describe each of these modeling approaches and their applicability to questions and topics of interest in organizational diversity and inclusion research. Additionally, we present a more detailed account of selected exemplar models from our review that utilized these two approaches to highlight the core concepts, process mechanisms, and emergent/dynamic outcomes they considered as well as some of the key takeaways/insights they afforded. Table 2 provides the list of published computational models identified in our review categorized by their modeling approach.

Neural Network/Connectionist Models

As the name implies, neural network models (also referred to as connectionist models) approximate the way in which neurons in the brain connect and interact with one another to process information (Rumelhart & McClelland, 1986). Neural network models are comprised of

[1] It should be noted that computational models often blend and borrow features of different modeling approaches. For example, an agent-based model can be constructed in which the decision rules governing how agents behave and interact are represented using a neural network. Or a systems dynamics model may be constructed that consists of distinctive agents carrying out simultaneous and interacting feedback loops. To facilitate the present discussion, we attempted to categorize the reviewed studies based on the singular model type we felt it most clearly represented.

nodes linked together through a configuration of *weighted connections*. The nodes in a neural network model often represent core concepts from a theory (e.g., perceptions about a target's cognitive ability), properties of the context being modeled (e.g., a target's gender, situational cues), or actions that the modeled system could take (e.g., select the male candidate). At any given time, nodes in a neural network exist in varying degrees of "activation," reflecting the extent to which the concept, property, or action represented by that node is present and/or currently operating. The pattern of interconnections among nodes allows the activation strength of different nodes to propagate throughout the neural network. These connections may be *directional* (i.e., unidirectional influence between nodes) or *bidirectional* (i.e., parallel/simultaneous influence between nodes), and *excitatory* (i.e., the activation of a node increases the likelihood of activating other nodes that it targets) or *inhibitory* (i.e., the activation of a node decreases the likelihood of activating other nodes that it targets). The connections feeding into a node are processed through an *activation function* that combines the strength of all incoming "signals" from the environment and other nodes which feed into it to determine that node's activation strength (e.g., the activation strength for the node "target has high math ability" depends on the activation strengths of the nodes "target is male" and the node "target is female" which feed into it). Random noise/error is also often incorporated into these activation functions to represent imperfections or other unregulated errors in the processing unit. In sum, the propagation of and competition among activation strengths across the nodes of a neural network and the network's pattern of interconnections allow for unique and dynamic activation patterns to emerge as signals flow between nodes.

These properties of neural networks can be configured and leveraged in specific ways to model several interesting types of phenomena. For example, *recurrent neural network models* are commonly used for classification applications in which the goal is to represent how a stimulus should be assigned to one or more categories based on its features. For example, a recurrent neural network model could be used to model how individuals make attributions about a target based on that target's demographic characteristics or how different situational and environmental cues influence social categorization. In contrast, *feed-forward neural networks* are frequently used for predictive or decision modeling in which the goal is to represent how a selection among alternatives is made. A feed-forward neural network could thus be used to model an individual's preference for affiliating with others based on their group membership or how he/she allocates resources to others based on different social factors.

Applications of neural network models in diversity and inclusion research have primarily been used to represent dynamic outcomes related to stereotyping and prejudicial attitudes. For example, Ehret, Monroe, and Read (2015) present a model that describes the cognitive processes underlying the emergence of stereotypes about oneself and others. Similarly, Freeman and colleagues (e.g., Freeman & Ambady, 2011; Freeman & Johnson, 2016; Freeman, Penner, Saperstein, Scheutz, & Ambady, 2011; Freeman, Stolier, Brooks, & Stillerman, 2018) have carried out an impressive stream of research that combines neural network modeling with physiological, behavioral, and neuroimaging data to examine the formation, representation, and influences on stereotype attributions. Below we summarize the neural network model constructed by these authors and its application to demonstrate the types of insights this modeling approach can afford.

Exemplar model. Freeman and Ambady (2011) discuss how neural network models can be used to represent person construal (i.e., how individuals develop evaluative perceptions of a target and its attributes) and more specifically the processes associated with stereotyping. Figure 1 presents a simplified depiction of one such neural network model from Freeman et al. (2011) depicting how stereotypes, visual cues, and situational demands can interact to influence individuals' social categorization judgments. The nodes in this neural network represent core concepts proposed by the authors as relevant to how people interpret and use information from the environment to infer the social category (e.g., race, occupation) of a target. The nodes are further organized into distinctive clusters (i.e., cue level, category level, etc.) that reflect their functional role in this process.

The pattern of excitatory and inhibitory connections among nodes in Freeman et al.'s (2011) model reflect how signals/information from the environment and their interpretation are proposed to influence the activation of these concepts to dynamically generate perceptions about a target. For example, visual input (cue level signals, bottom row in Figure 1) such as the skin color and type of clothing worn by a target are proposed to activate nodes representing the perceiver's beliefs about the target's race and occupation, respectively (category level signals, second row from bottom in Figure 1). Of note, nodes *between* functional levels in this neural network model are linked via excitatory connections (e.g., activating the "White" node at the category level increases the likelihood of activating the "High-Status" node at the stereotype level), whereas nodes *within* functional levels are linked via inhibitory connections (e.g., activating the "White" node at the category level decreases the likelihood of activating the "Black" node at this same level). The excitatory vertical connections reflect the theoretical proposition that particular beliefs/sources of information tend to positively correlate (e.g., a person wearing a suit is likely to work in business), whereas the inhibitory lateral connections reflect that different attributes within a given functional cluster tend to be negatively correlated and/or mutually exclusive (e.g., a person who works in business is not likely to also work as a janitor). Furthermore, these connections possess weights that reflect the strength of activation between any two nodes; the stronger the association between nodes at the category level (e.g., "White") and nodes at the stereotype level (e.g., "High-Status"), the more likely it is that one's perception of a target's race will activate particular stereotypical attributions about that target.[2]

[2] To simplify the current model description, we do not describe all parameters/features of the activation functions used in the model shown in Figure 1 (e.g., resting activation value for nodes, decay parameters, scaling constants). See Freeman et al. (2011) and Freeman and Ambady (2011) for a more complete description of this model's parameterization.

As one example of how the dynamics in Freeman et al.'s (2011) neural network model unfold, consider an observer who is shown an image of a target person with prototypically Black facial features but no visual cues that would suggest their occupation. Figure 1 indicates that these specific visual cues make it more likely that the perceiver would categorize the target person as "Black" while simultaneously suppressing their categorization as "White." This activation pattern carries through to the stereotype level, such that activation of the "Low-Status" category is increased via both the direct excitatory connection between Black ↔ Low-Status and the sequence of excitatory and inhibitory connections between White ↔ High-Status ↔ Low-Status (i.e., target is not likely to be White, thus making them less likely to be High-Status and more likely to be Low-Status). The pattern of connections that exist between those stereotype attributions and occupational categories also make it more likely that the "Janitor" node will be activated (via the excitatory connection from Low-Status ↔ Janitor and the sequence of excitatory and inhibitory connections between High-Status ↔ Business person ↔ Janitor). Consequently, Freeman et al.'s (2011) neural network model both describes and predicts why individuals would be more likely to associate certain social categories with particular demographic groups even in the absence of information about that target's social category (e.g., a target perceived as Black is more readily classified as a Janitor rather than a Business Person)—a commonly observed empirical finding in research examining race-based stereotyping and categorization (e.g., Eberhardt, Goff, Purdie, & Davies, 2004).

The neural network model shown in Figure 1 also provides an account for the reverse—and arguably more counterintuitive—inference that social status cues can systematically bias perceptions of a target's race. To demonstrate, Freeman et al. (2011) discuss findings from two empirical studies in which participants were tasked with categorizing the race of different faces whose features were morphed along a continuum from prototypically White to prototypically Black and shown as wearing either high-status (i.e., suit and tie) or low-status (i.e., janitor jumpsuit) attire. Findings from their research revealed that (a) depicting a face with low-status attire tended to increase the likelihood of categorizing that face as Black; (b) depicting a face with high-status attire tended to increase the likelihood of categorizing that face as White; and (c) the influence of attire on racial categorization grew stronger as the facial features of the target other became more racially ambiguous (i.e., face less prototypically Black or White). The authors subsequently recreated this experimental paradigm using the neural network model shown in Figure 1 and observed that their simulation results replicated the empirical result patterns almost perfectly (R^2 between model and empirical data = .99). Further, they were able to use their model to elaborate how seemingly innocuous social context cues related to attire could influence perceptions of race when facial features were ambiguous. In terms of the neural network model, the presentation of racially ambiguous facial features means that the "White" and "Black" category nodes are activated to nearly equal levels. Thus, neither category emerges as dominant based on those cues alone. Consequently, the sequence of excitatory and inhibitory connections that connects social context cues (i.e., attire) to occupation to social status stereotypes and eventually to demographic categories (attire → occupation ↔ status ↔ race) results in social context cues playing a more decisive role in determining the categorization of a face as White or Black. In sum, Freeman et al.'s (2011) neural network model provides a compelling demonstration that even a relatively simple computational model can offer a powerful investigatory tool for unpacking a central topic of interest to organizational diversity and inclusion researchers.

Agent-Based Models

While neural network models tend to focus on within-individual processes, agent-based models (ABMs) tend to emphasize how the interactions between individuals in a social system give rise to emergent patterns and structures at a collective level (Wilensky & Rand, 2015). All ABMs are composed of three fundamental elements: *agents, environments,* and *rules*. Agents are the focal units/entities of interest in a phenomenon (e.g., individuals, teams, organizations) and possess attributes or states that may be either static (e.g., race, sex, personality) or allowed to change over time (e.g., perceptions, goals, motivation levels). The properties of agents or their distribution in a population of agents often represent core concepts of a theory (e.g., race, status, group membership). Environments in an ABM represent the embedding contexts in which agents exist and interact. Depending on the phenomena of interest, attributes of an environment may change over time and/or as a result of agent behavior (e.g., as individuals use environmental resources). In many cases, environmental properties in an ABM include constraints that influence what behaviors or interactions an agent can perform (e.g., interdependence networks that determine who works with whom, positions/roles that agents may occupy).

Lastly, rules in an ABM describe the procedures that agents and environments follow or enact over time. The rules instantiated in an ABM typically reflect the core process mechanisms of a theory and are represented in the form of logic and/or simple mathematical functions that determine how, when, and to what extent agents act, interact, and change (e.g., if two interacting agents hold differing opinions, then their perceptions towards one another change by X). Through repeated enactment of rules by the agents in an ABM, unique structures/properties at the collective level (e.g., segregation of agents into distinct clusters, group norms) can emerge "bottom-up" through agent-agent and agent-environment interactions. These emergent properties can also exert a "top-down" influence on future behavior/interaction, thus reflecting the reciprocal micro ↔ macro relationship inherent in complex social systems (Page, 2018).

Given that many phenomena of interest in the diversity sciences involve social interaction, it is not surprising that our review revealed ABMs as the most frequently used modeling technique by diversity and inclusion researchers. Extant ABMs have spanned several conceptual levels and foci of interest, including the consequences of stereotypes at the individual level (e.g., Schroder, Hoey, & Rogers, 2016), in-group/out-group formation (e.g., Gray et al., 2014; Flache & Macy, 2011), and organizational segregation/stratification (e.g., Abdou & Gilbert, 2009; Martell, Lane, & Emrich, 1996). ABMs have also been used to supplement social network data/methodologies in the study of diversity-related topics. For example, both Alvarez-Galvez (2016) and Sohn and Geidner (2015) used ABMs to elaborate on how social network structure and related contextual factors influence the spread of minority opinions throughout a social system, a phenomenon commonly discussed in the literature on social inclusion, voice, and multiculturalism as the “spiral of silence” (Bowen & Blackmon, 2003; Gawronski, Nawojczyk, & Kulakowski, 2014; Ringelheim, 2010).

Owing to the larger breadth of existing diversity-related ABMs and the recognition that between-person processes often lie at the core of diversity and inclusion theories and research, we elected to elaborate on two ABMs in greater detail that focus on different phenomena and levels of analysis. The first is a meso-/group-level ABM developed by Flache and Mäs (2008a; 2008b) examining the emergence of team consensus as a function of team diversity composition. The second is a macro-/organization-level ABM developed by Samuelson, Levine, Barth, Wessel, and Grand (2019) that focuses on the emergence of gender disparities within senior organizational leadership positions.

Group-level exemplar model. Lau and Murnighan’s (1998) seminal work on team faultlines posits that teams in which members can align themselves into demographically homogenous subgroups are at greater risk for divisiveness, disagreement, and poor communication patterns that hold negative implications for team performance. Lau and Murnighan (1998) suggest that these outcomes emerge because (a) individuals prefer to interact with similar others (i.e., *homophily*) and (b) the opinions/beliefs of individuals tend to adapt to one another following interactions (i.e., *social influence*). Played out over time, these mechanisms can “fracture” a team with strong faultlines into subgroups wherein members tend to primarily interact with and learn from those who share similar demographics, beliefs, and perspectives. These fractured teams are subsequently less likely to benefit from or leverage the unique resources or capabilities afforded by their diverse members when carrying out job tasks and goals (e.g., Hong & Page, 2004; Lau & Murnighan, 2005).

Although Lau and Murnighan (1998) offer a narrative account of how team faultlines can breed polarization in groups, Flache and Mäs (2008a; 2008b) note that several assumptions of this theory were not well specified. Most notably, Flache and Mäs (2008b) contend that for the proposed homophily and social influence mechanisms to create dissensus in teams along demographic faultlines, it must also be true that demographically similar individuals hold similar beliefs and opinions.[3] Flache and Mäs (2008b) suggested that while a correlation between demographic membership and beliefs may exist, it only represents a sufficient (but not necessary) condition for belief polarization to emerge in teams. To this end, the authors described two additional processes that likely also contribute to belief polarization and act in parallel with homophily and social influence: *heterophobia* (individuals actively avoid/dislike individuals who are not like them) and *rejection* (individuals change their opinions/beliefs in ways that make them less similar to those they do not like). Together, these four mechanisms operate such that individuals are more attracted to and adopt beliefs similar to like others (homophily + social influence) while being simultaneously repelled and adopting beliefs different to unlike others (heterophobia + rejection). Importantly, these mechanisms would not require different demographic affiliations to be associated with particular beliefs/opinions for fracturing to emerge along team faultlines.

To evaluate their propositions, Flache and Mäs (2008b) developed an ABM to examine the extent to which (a) their additional mechanisms were sufficient to generate faultline-induced polarization of beliefs in simulated agent teams and (b) stronger faultlines tend to lead to stronger within-team dissensus as observed in existing empirical data (Lau & Murnighan, 1998, 2005). Table 3 summarizes the *pseudocode* (i.e., non-technical summary of the steps carried

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[3] Without this condition, demographically similar individuals might still be more likely to interact with one another due to homophily. However, if beliefs were randomly distributed across different demographic groups, there would be no guarantee that social influence processes—which are proposed to "push" the beliefs of interaction partners together—would lead to multiple demographically homogenous subgroups that hold different beliefs. In other words, it would be just as likely for demographically homogenous subgroups that hold *similar* beliefs to emerge as those that hold dissimilar beliefs.

out to run a computational model) of their model. In brief, a simulated team of *N* individuals is constructed in which each agent contains *D* “fixed” variables (representing categorical demographic characteristics) and *K* “flexible” variables (representing work-related opinions/beliefs). A method for initializing teams with differing levels of faultline strength is then implemented. Most significantly, this operationalization is such that increasing faultline strength increases the extent to which the distribution of *D* categorical variables across agents produces more demographically homogenous clusters within a team while ensuring the distribution of *K* continuous beliefs across agent members is random (i.e., *D* and *K* are uncorrelated). Lastly, all simulated team members are made to exist in a fully connected, directional, asymmetric social influence network such that the strength of influence between any two agents is proportional to the similarity between those agents’ standing on their *D* and *K* variables.

The effects of interactions within the agent team in the model are then simulated by randomly selecting a single agent and having that agent either (a) update all of its *K* work-relevant beliefs or (b) update all of its influence ties. The extent to which an agent changes its standing on a given *K* attribute was made proportional to the sum of the differences between the selected agent’s and each other agents’ standing for that attribute, weighted by the strength of the influence ties linking agents.[4] An agent’s dyadic influence tie was changed in a similar fashion such that each tie changed in proportion to the similarity between that agent’s and a given target agent’s current standing on the *D* and *K* variables. Taken together, both of these formulations represent agents tending to have their *K* beliefs “pulled” into alignment with those of agents whom they perceive as similar/influential (i.e., homophily + social influence) and “pushed” out of alignment from those they perceive as dissimilar/uninfluential (i.e., heterophobia + rejection) as a result of their interactions. In each model step, this simulated interaction

[4] The actual updating function used by Flache and Mäs (2008b) divided this weighted sum by 2 to represent a more gradual change in opinions. The authors also included a modification to ensure that the values for a_{ik} could not go out of bounds and to smooth the gradient change as they approached the extreme bounds of the scale.

process and updating of agent beliefs or influence ties are carried out *N* times, after which several aggregate variables representing the team's polarization across the *K* opinion/belief variables are recorded. This entire procedure is then repeated several hundred times to provide all agents in the team sufficient opportunity to interact and allow any potential patterns of consensus and/or dissensus to emerge dynamically.

In their initial simulations, Flache and Mäs (2008b) demonstrated that their model specification produced results qualitatively consistent with those posited by Lau and Murnighan (1998). Agent teams with stronger faultlines tended to produce stronger belief polarization along demographic clusters (i.e., emergence of subgroups composed of agents whose *D* attributes and *K* beliefs were diametrically opposed), thus demonstrating that a correlation between demographic membership and beliefs was not necessary for faultlines to fracture a team. Perhaps more importantly, the authors were also able to use the model to probe *how* this fracturing unfolded. Flache and Mäs (2008b) observed that the polarization dynamics produced under the assumptions of their model tended to be strongly driven by agents with different demographic profiles that initially held more extreme (as opposed to more moderate) beliefs. These "opposing extremists" had the effect of disproportionately pulling other demographically similar agents towards their extreme views (homophily + social influence) while simultaneously widening the gulf that existed between their views and those of demographically different agents (heterophobia + rejection). In tandem, these forces created a positive feedback loop that eventually led to the emergence of demographically homogenous subgroups with highly shared but opposite views.

Given these observations, the authors posited that it might be possible to counteract these polarization dynamics by attempting to control *which* agents interacted and *when*. Flache and Mäs (2008a) pursued this question in a separate simulation study by modifying the structure of agent interactions. In one simulated condition, agents were initially allowed to interact *only* in small demographically homogenous subgroups for a period of time before being allowed to interact with all other agents on the team. In a second simulated condition, agents were initially allowed to interact *only* in small demographically heterogeneous subgroups for a period of time before being allowed to interact with all other agents on the team.[5] Counter to prevailing predictions of intergroup contact theory which suggest that differences between groups can be reduced through interaction (e.g., Allport, 1954; Pettigrew, 1998), the results of Flache and Mäs's (2008a) simulation revealed that agent teams initially structured into demographically homogenous subgroups achieved complete belief consensus even under very strong faultlines, whereas agent teams initially organized into demographically heterogeneous subgroups resulted in near-total belief polarization even under very weak faultlines.

The explanation for this counterintuitive result pattern is rooted in Flache and Mäs's (2008b) previous observations regarding how "extremist" agents tend to influence the beliefs of other team members. In the simulated conditions where agents were restricted to first interacting in demographically homogenous subgroups, the initial lack of any highly dissimilar interaction partners meant that agents with more extreme views had no visible "opponents" to push further away from. As a result, the beliefs of those extreme agents could be pulled towards the (usually more moderate) views of their demographically similar counterparts. Over time this process resulted in a set of localized beliefs emerging within *each* subgroup that tended to be more moderate in position. When the subgroup structures were disbanded and the entire team finally allowed to interact, the entire team of agents now possessed a set of beliefs that were likely to be only moderately different and therefore more easily overcome despite any demographic dissimilarities. In contrast, initially organizing agents into more demographically heterogeneous subgroups ensured that agents with more extreme views would have a demographically dissimilar opponent to begin pushing away from immediately, thus

[5] Flache and Mäs (2008a) analogized these two scenarios to creating "caves" within which different subsets/subgroups of agents within a team would interact before all the caves were joined into one. However, the researchers still manipulated *team-level faultline strength* in the same fashion as in the initial simulations (cf., Flache & Mäs, 2008b), thus providing a common base of comparison.

exacerbating any preexisting differences and creating polarized clusters of beliefs localized within each subgroup. Once the subgroup structure was disbanded, agents could find others within the broader team environment who shared their now entrenched and more extreme beliefs, leading to rapid team-wide dissensus. In sum, interacting in the smaller but more demographically homogenous subgroups before interacting in the larger but more demographically diverse team setting tended to "temper" the views of agents with more extreme positions who would have otherwise created a divisive wedge within the team. In contrast, interacting in the smaller but more demographically heterogeneous subgroups tended to "radicalize" the views of agents towards more extreme positions that virtually ensured a fractured team. Although these patterns of simulated findings require empirical examination before concluding their validity, Flache and Mäs (2008a; 2008b) provide a compelling demonstration of the power of ABMs for probing theory, unpacking complex social processes, and advancing intriguing new predictions relevant to diversity researchers.

Organization-level exemplar model. The lack of female representation among senior organizational leadership has long been cited as an area of concern in the contemporary workforce (Silva, Carter, & Beninger, 2012), and significant theoretical and empirical attention has been directed towards describing and rectifying its believed root causes. A significant challenge for researchers, practitioners, and policymakers in addressing this issue, however, is that the obstacles which are likely to impede female employees' efforts to equitably rise through the organizational ranks exist and dynamically interact across several levels of analysis (i.e., individual, organizational, sociocultural) in ways that are difficult to study empirically (Eagly & Carli, 2007). To this end, Samuelson et al. (2019) describe an ABM intended to serve as a computational framework and testbed for exploring the simultaneous impact of multiple factors across different system levels that could plausibly impede female representation in organizational leadership positions.

The pseudocode for Samuelson et al.'s (2019) model is summarized in Table 4.[6] At its core, the ABM models a simple performance → turnover → selection → promotion cycle for employee agents within a single hierarchically arranged organization. A group of agents are first created and assigned several attributes, such as gender, ability, and age; these agents represent an organization's "original" employee population. Once constructed, the agents are then simulated as accumulating job performance/experience by completing tasks assigned to them each month. At the end of a simulated year, some agents may decide to voluntarily turnover from the organization as a function of several factors (e.g., age, time since last promotion). A percentage of these recently vacated positions are then filled by hiring new agents into the organization, after which the top-performing incumbent agents within each level of the organization are promoted to fill any remaining positions at the next highest level of the organizational hierarchy. This entire performance → turnover → selection → promotion cycle is repeated until none of the original agent employees exist, thus ensuring that any processes which could influence the distribution of male and female agents within the organization (e.g., promotion, selection) have had sufficient opportunity to play out.

Within these core process mechanisms, Samuelson et al. (2019) incorporated several other elements proposed to disproportionately affect female employees' chances of reaching positions of senior leadership in an organization. For example, all simulated agents had the same fixed probability of experiencing a "career delay"—representing that an individual might need to leave their job for medical or family reasons—which would prevent them from accumulating experience/performance important for promotions. However, and consistent with family and medical leave data from the United States (Klerman, Daley, & Pozniak, 2012), the average delay for female agents was made longer than that of male agents, thus resulting in the potential for female agents to fall slightly behind their male counterparts with respect to job-

[6] The full model code and all simulated data reported in Sameulson et al. (2019) are available for download at https://github.com/grandjam/SamuelsonEtAl_GenderStratModel.

relevant experience. Additionally, female agents could experience negative consequences associated with tokenism (the experience of being a member of a social minority amongst a dominant majority; Kanter, 1977), which increased their likelihood of voluntarily leaving an organization if male agents became disproportionately overrepresented (King et al., 2009).

Beyond these core model mechanisms, Samuelson et al. (2019) were particularly interested in examining the effects of two factors that have received significant attention as drivers of organizational gender stratification: (1) differences in the *hiring rate* of males versus females into an organization, and (2) providing more valuable *developmental opportunities* to males versus females (i.e., more visible or important jobs, tasks, opportunities, etc. that tend to correlate with upward organizational mobility; Silva et al., 2012). These factors were subsequently incorporated into Samuelson et al.'s (2019) model specification, and a series of simulation studies that manipulated these core mechanisms were carried out to examine their impact on the distribution of male and female agents within an organization's hierarchy.

The results of Samuelson et al.'s (2019) simulations revealed several unique insights into the possible dynamics of gender stratification within organizational leadership. For example, although differences in the hiring rates of male and female agents exhibited a clear and obvious impact on which employees *entered* an organization, it also exerted a less obvious—but still sizable effect—on which employees *left* an organization. Organizations that tended to hire more male than female agents eventually triggered a "tipping point" wherein experiences of tokenism for female agents become so commonplace that female agents began to turnover from the organization in higher numbers. Paired with the greater likelihood of then hiring new male agents to replace the vacancies created by departing female agents, these dynamics created a positive feedback loop resulting in even lower representation of women in leadership positions than would be expected based on the external hiring rates of males versus females alone.

A similar pattern was observed with respect to the impact of developmental opportunity differences for male and female agents. In Samuelson et al.'s (2019) model, agents completing a developmental opportunity received a “boost,” representing the opportunity’s higher value, to their job performance/experience relative to completing their typical job tasks. Because agents with the highest accumulated performance were “first in line” for promotions, completing developmental opportunities was crucial in determining which agents advanced up the organizational hierarchy. Although both male and female agents in Samuelson et al.’s (2019) simulations were afforded the same *number* of developmental opportunities, the *value* of developmental opportunities given to males was made to be higher than those given to females. The apparent effect of this difference is that male agents tended to accumulate higher levels of performance/experience more rapidly than female agents over time, and thus receive more promotions. However, an additional effect of these opportunity differences was that female agents tended to be held back in the lower levels of the organization for comparatively long periods, a phenomenon some diversity researchers have labeled the “sticky floor” effect (e.g., Booth, Francesconi, & Frank, 2003; Yap & Konrad, 2009). Given that a sustained lack of upward mobility and advancement over time further contributed to an agent’s likelihood of turning over in the model, the sticky floor generated by developmental opportunity differences also increased the turnover rate for female agents and thus made it even more unlikely that female agents would reach senior leadership positions. In sum, Samuelson et al.’s (2019) ABM of gender stratification offers an interesting demonstration of how computational modeling can usefully integrate theoretical concepts, empirical observations, and policies across multiple system levels to examine complex organizational dynamics of relevance to diversity and inclusion researchers.

Extensions and Future Directions

Before concluding our discussion of computational modeling applications in diversity and inclusion research, we wish to take the opportunity to use the models by Freeman et al. (2011), Flache and Mäs (2008b) and Samuelson et al. (2019) described above to highlight one final advantage of computational modeling—the potential to build upon their specifications to integrate, advance, and explore new knowledge. Although computational modeling requires researchers to more precisely formalize the core concepts, process mechanisms, and emergent/dynamic outcomes integral to their theory, all such models—including those reviewed here—reside on specific assumptions, simplifications, operationalizations, and boundary conditions that necessarily shape the conclusions and insights that can be drawn from them. These choices mark essential elements for future work to examine and consider ways of improving or extending through additional theory development, empirical verification, and model refinement (Grand, Braun, Kuljanin, Kozlowski, & Chao, 2016; Kozlowski, Chao, Grand, Braun, & Kuljnain, 2013). In this spirit, we briefly consider ways in which the previously reviewed models might be further developed to explore additional questions of interest to diversity and inclusion scholars.

Neural network models of stereotyping. Given the considerable empirical validation that has been conducted with Freeman et al.'s (2011) neural network model, we believe this computational architecture could offer a valuable platform for expanding into additional topics of interest to organizational scientists that involve stereotyping, prejudice, and discrimination. One fruitful pursuit could be integrating a form of Freeman et al.'s (2011) model with theories of leader emergence. The leader emergence literature has long suggested that identifying another individual as a leader and "granting" them influence is consistent with social categorization and confirmation process (e.g., Acton, Foti, Lord, & Gladfelter, 2019; DeRue & Ashford, 2010; Lord, Foti, & De Vader, 1984; Nye & Forsyth, 1991). In other words, an individual's leadership status is proposed to be dependent on the extent to which the expression and interpretation of their attributes, behaviors, etc. are consistent with the expectations and stereotypes regarding what followers believe a leader should be like.

Although some leadership scholars have discussed the application of connectionist frameworks as a representation of the leader emergence process (e.g., Lord, Brown, Harvey, & Hall, 2001), Freeman et al.'s (2011) neural network model provides a relatively straightforward and highly generalizable means for representing and empirically examining how particular expressions and features of an individual might impact the categorization of that person as a leader. For example, research has demonstrated that demographic categories, such as race and gender, are incorporated into individuals' expectations about leadership and impact their categorization of others as leaders (e.g., Forsyth, Heiney, & Wright, 1997; Livingston, Rosette, & Washington, 2012; Rosette, Leonardelli, & Phillips, 2008; Rosette & Tost, 2010; Scott & Brown, 2006). These propositions have even been integrated into narrative conceptualizations of the influence of race and gender on leader categorization (Hogue & Lord, 2007; Sy et al., 2010). However, these treatments and discussions have not attempted to formalize these mechanisms into a precise or testable theoretical account. Additionally, attempting to develop such a model would allow a deeper investigation into how the intersectionality of demographic categories (e.g., race *and* gender) impact the leadership claiming and granting process. Existing work in the diversity sciences (e.g., Rosette, Koval, Ma, & Livingston, 2016) suggests that such intersections are likely to result in leader emergence effects that are complex and difficult to predict across people and conditions—circumstances in which computational modeling and simulation techniques are often beneficial.

Agent-based modeling of team faultlines. Flache and Mäs's (2008a; 2008b) ABMs on team faultlines primarily focuses on how visible and recognizable demographic attributes can affect subgroup formation within teams. However, we believe the basic processes represented by their model and outlined in Table 3 could also provide a foundation for advancing research and theory development around identity management and disclosure within groups, particularly for those with less visible and stigmatized identities (i.e., sexual minorities, religious minorities, mental illness diagnosis; Ellison, Russinova, MacDonald-Wilson, & Lyass, 2003; Ragins, Singh, & Cornwell, 2007; Sabat, Lindsey, King, & Ahmad, 2017).

One particularly intriguing development we could envision is the use of Flache and Mäs's (2008a; 2008b) ABMs to explore how demographic faultlines could interact with individuals' choices to disclose their identity and, vice versa, the downstream effects of such disclosure on group cohesion. Emerging empirical evidence suggests that individuals often make very different disclosure decisions to their team and organizational members based on their interaction partners (King, Mohr, Peddie, Jones, & Kendra, 2017; Wessel, 2017), but the mechanisms involved in this process are still not well explicated. However, by building upon the mechanisms specified in Flache and Mäs (2008b) and other models on opinion formation and communication privacy management (e.g., Petronio, 2002), the choice of which and with whom to share information about one's stigmatized identity as well as how that information might shape team climates, functioning, and performance within an organization could also be modeled. This possible extension also highlights how efforts to develop and refine a computational model on one particular topic (e.g., identity management) may also simultaneously push the state of science and practice in other areas as well (e.g., team effectiveness).

Agent-based modeling of organizational stratification. Although Samuelson et al.'s (2019) ABM focused more specifically on the effects of hiring rates and developmental opportunity differences as explanations for the underrepresentation of female leaders, their basic model architecture is built upon a simple yet highly flexible representation of personnel practices and human capital flow in organizations (e.g., performance → turnover → selection → promotion cycles). Consequently, this core process could be easily expanded to incorporate the role that other personnel management techniques (e.g., recruitment, performance evaluation, training) might play in exacerbating or attenuating gender stratification in organizations. Furthermore, expanding the "ecosystem" represented in Samuelson et al.'s (2019) ABM could also afford unique opportunities to explore additional contributors to and possible remedies for demographic stratification. For example, expanding the model to be able to represent multiple organizations and allowing agents to move *between* organizations—rather than only into or out of a *single* organization—would afford the ability to examine how inter- versus intraorganizational mobility might differentially affect the prospects of male and female employees for attaining leadership positions (e.g., Favaro, Karlsson, & Nelson, 2014; Valcour & Tolbert, 2003).

In addition to the potential to broaden Samuelson et al.'s (2019) model to address moves between organizations, the model could also be expanded to address agent actions prior to organizational entry. A commonly cited reason for the lack of diversity in organizational leadership is the “leaky pipeline”, or the notion that members from underrepresented groups are often lost at various points along the path from schooling to career development (e.g., Ahmad & Boser, 2014; Blickenstaff, 2005; Gasser & Shaffer, 2014; Monforti & Michelson, 2008). This proposition implies that demographic stratification in organizations is likely not only a matter of what happens *in* organizations, but also has antecedents that stretch as far back as the development and maintenance of interests and recruitment practices that help to develop individuals of diverse races, genders, and socioeconomic statuses (Offermann, Thomas, Lanzo, & Smith, 2019). A computational model of organizational stratification capable of representing these additional mechanisms would not only serve as a useful tool for researchers to integrate the broad streams of work relevant to understanding the leaky pipeline, but could also be used to advise policymakers and organizational decision-makers about where and how to invest resources to improve demographic representation across all levels of the workforce.

Conclusion

Our primary aims for this chapter were to provide organizational researchers and practitioners interested in diversity and inclusion topics with (a) an understanding of the value of computational modeling for pursuing domain-relevant questions; (b) an entry point for how to approach organizational diversity-related research and practice from a more computational perspective; and (c) examples of computational modeling efforts relevant to organizational diversity and inclusion that highlight the potential for advancing unique insights and predictions. The topics and issues pursued by diversity and inclusion researchers are as varied as the people, groups, and cultures to whom they apply. We see many opportunities to leverage the strengths of computational modeling to aid the study and improvement of these organizationally and societally important issues. We hope this chapter will encourage more organizational diversity researchers and practitioners to both consider and utilize computational modeling techniques as a valuable tool in the pursuit of knowledge and policies that promote fair, equitable, and respectful treatment of all employees and individuals.

REFERENCES

Abdou, M., & Gilbert, N. (2009). Modelling the emergence and dynamics of social and workplace segregation. *Mind & society*, *8*(2), 173.

Acton, B.P., Foti, R.J., Lord, R.G., & Gladfelter, J.A. (2019). Putting emergence back in leadership emergence: A dynamic, multilevel, process-oriented framework. *The Leadership Quarterly, 30*(1), 145-164.

Adler, R.D. (2001). Women in the executive suite correlate to high profits. *Harvard Business Review, 79*, 30.

Ahmad, F. Z., & Boser, U. (2014). America's Leaky Pipeline for Teachers of Color: Getting More Teachers of Color into the Classroom. *Center for American Progress*.

Allport, G. W. (1954). *The nature of prejudice*. Reading, MA: Addison-Wesley.

Al Ramiah, A., Hewstone, M., Dovidio, J. F., & Penner, L. A. (2010). The social psychology of discrimination: Theory, measurement, and consequences. In H. Russell, L. Bond, & F. McGinnity (Eds.), *Making equality count: Irish and international approaches to measuring discrimination* (pp. 84-112). Dublin, Ireland: Liffey Press.

Alvarez-Galvez, J. (2016). Network models of minority opinion spreading: Using agent-based modeling to study possible scenarios of social contagion. *Social Science Computer Review*, *34*(5), 567-581.

Axelrod, R. (1997). The dissemination of culture: A model with local convergence and global polarization. *Journal of Conflict Resolution, 41*, 203-226.

Berscheid, E., & Hatfield, E. (1969). *Interpersonal attraction*. Reading, MA: Addison-Wesley.

Blalock, H.M. (1967). *Toward a theory of minority-group relations*. New York, NY: Wiley.

Blau, P.M. (1977). *Inequality and heterogeneity: A primitive theory of social structure*. New York, NY: Free Press.

Blickenstaff, J.C. (2005). Women and science careers: leaky pipeline or gender filter? *Gender and Education*, *17*(4), 369–386.

Bonacich, E. (1972). A theory of ethnic antagonism: The split labor market. *American Sociological Review*, *37*(5), 547-559.

Booth, A., Francesconi, M., & Frank, J. (2003). A sticky floors model of promotion, pay, and gender. *European Economic Review, 47*, 295–322.

Bowen, F., & Blackmon, K. (2003). Spirals of silence: The dynamic effects of diversity on organizational voice. *Journal of management Studies*, *40*, 1393-1417.

Byrne, D. (1971). *The attraction paradigm*. New York, NY: Academic Press.

Catalyst (2004). The Bottom Line: Connecting Corporate Performance and Gender Diversity. Catalyst: New York.

Colella, A.J., Hebl, M., & King, E. (2017). One hundred year of discrimination research in the *Journal of Applied Psychology*: A sobering synopsis. *Journal of Applied Psychology, 102,* 500-513.

Colella, A.J., McKay, P.F., Daniels, S.R., & Signal, S.M. (2012). Employment discrimination. In S.W.J. Kozlowski (Ed.), *The Oxford Handbook of Organizational Psychology, Vol. 2*. (pp. 1034-1102). Oxford, UK: Oxford University Press.

Crenshaw, K. (1989). Demarginalizing the intersection of race and sex: A Black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics. *University of Chicago Law Forum*, *1989*, 139–168.

Cuddy, A. J. C., Fiske, S. T., & Glick, P. (2008). Warmth and competence as universal dimensions of social perception: The stereotype content model and the BIAS map. In M. P. Zanna (Ed.), *Advances in experimental social psychology, Vol 40.* (Vol. 40, pp. 61–149). San Diego, CA: Elsevier Academic Press.

Davis, J.P., Eisenhardt, K.M., & Bingham, C.B. (2007). Developing theory through simulation methods. *Academy of Management Review, 32*, 480-499.

DeRue, D. S., & Ashford, S. J. (2010). Who will lead and who will follow? A social process of leadership identity construction in organizations. *Academy of Management Review, 35*(4), 627-647.

Eagly, A.H., & Carli, L.L. (2007). Women and the labyrinth of leadership. *Harvard Business Review, 85*, 62-71.

Eberhardt, J.L., Goff, P.A., Purdie, V.J., & Davies, P.G. (2004). Seeing Black: Race, crime, and visual processing. *Journal of Personality and Social Psychology, 87*, 876-893.

Ehret, P. J., Monroe, B. M., & Read, S. J. (2015). Modeling the dynamics of evaluation: A multilevel neural network implementation of the iterative reprocessing model. *Personality and Social Psychology Review*, *19*(2), 148-176.

Ellison, M. L., Russinova, Z., MacDonald-Wilson, K. L., & Lyass, A. (2003). Patterns and correlates of workplace disclosure among professionals and managers with psychiatric conditions. *Journal of Vocational Rehabilitation*, *18*(1), 3–13.

Favaro, K., Karlsson, P. O., & Neilson, G. L. (2014). The 2013 chief executive study: Women CEOs of the last 10 years. *Strategy&*.

Fields, D.L., & Blum, T.C. (1997). Employee satisfaction in work groups with different gender composition. *Journal of Organizational Behavior, 18*, 181-196

Flache, A., & Macy, M. W. (2011). Small worlds and cultural polarization. *The Journal of Mathematical Sociology*, *35*(1-3), 146-176.

Flache, A., & Mäs, M. (2008a). How to get the timing right. A computational model of the effects of the timing of contacts on team cohesion in demographically diverse teams. *Computational and Mathematical Organization Theory, 14*(1), 23-51.

Flache, A., & Mäs, M. (2008b). Why do faultlines matter? A computational model of how strong demographic faultlines undermine team cohesion. *Simulation Modeling Practice and Theory, 16*, 175-191.

Forsyth, D. R., Heiney, M. M., & Wright, S. S. (1997). Biases in appraisals of women leaders. *Group Dynamics: Theory, Research, and Practice, 1*(1), 98-103.

Freeman, J.B. & Ambady, N. (2011). A dynamic interactive theory of person construal. *Psychological Review, 118,* 247-279.

Freeman, J.B., & Johnson, K.L. (2016). More than meets the eye: Split-second social perception. *Trends in Cognitive Science, 20*, 362-374.

Freeman, J. B., Penner, A. M., Saperstein, A., Scheutz, M., & Ambady, N. (2011). Looking the part: Social status cues shape race perception. *PloS one, 6*(9), e25107.

Freeman, J.B., Stolier, R.M., Brooks, J.A., & Stillerman, B.S. (2018). The neural representational geometry of social perception. *Current Opinion in Psychology, 24*, 83-91.

Gasser, C. E., & Shaffer, K. S. (2014). Career development of women in academia: Traversing the leaky pipeline. *The Professional Counselor, 4,* 332-352.

Gawronski, P., Nawojczyk, M., & Kulakowski, K. (2014). Opinion formation in an open system and the spiral of silence. arXiv preprint arXiv:1407.2742.

Glicke, P., & Fiske, S. T. (2001). Ambivalent sexism. In M. P. Zanna (Ed.), *Advances in experimental social psychology, Vol. 33.* (pp. 115–188). San Diego, CA: Academic Press.

Grand, J. A. (2017). Brain drain? An examination of stereotype threat effects during training on knowledge acquisition and organizational effectiveness. *Journal of Applied Psychology, 102*(2), 115.

Grand, J.A., Braun, M.T., Kuljanin, G., Kozlowski, S.W.J., & Chao, G.T. (2016). The dynamics of team cognition: A process-oriented theory of knowledge emergence in teams [Monograph]. *Journal of Applied Psychology, 101*, 1353-1385.

Gray, K., Rand, D. G., Ert, E., Lewis, K., Hershman, S., & Norton, M. I. (2014). The emergence of “us and them” in 80 lines of code: Modeling group genesis in homogeneous populations. *Psychological Science, 25*(4), 982-990.

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review, 32*(4), 1199-1228.

Harrison, J.R., Lin, Z., Carroll, G.R., & Carley, K.M. (2007). Simulation modeling in organizational and management research. *Academy of Management Review, 32*, 1229-1245.

Harrison, D. A., Price, K. H., & Bell, M. P. (1998). Beyond relational demography: Time and the effects of surface- and deep-level diversity on work group cohesion. *Academy of Management Journal*, *41*(1), 96–107.

Harrison, D. A., Price, K. H., Gavin, J. H., & Florey, A. T. (2002). Time, teams, and task performance: Changing effects of surface- and deep-level diversity on group functioning. *Academy of Management Journal*, *45*(5), 1029–1045.

Hilton, J. L., & von Hippel, W. (1996). Stereotypes. *Annual Review of Psychology*, *47*, 237–271.

Hogue, M., & Lord, R. G. (2007). A multilevel, complexity theory approach to understanding gender bias in leadership. *The Leadership Quarterly, 18*(4), 370-390.

Hong, L., & Page, S.E. (2004). Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences, 101*, 16385-16389.

Jackson, L. M., & Hunsberger, B. (1999). An intergroup perspective on religion and prejudice. *Journal for the Scientific Study of Religion*, *38*(4), 509–523.

Joseph, K., Morgan, G. P., Martin, M. K., & Carley, K. M. (2014). On the coevolution of stereotype, culture, and social relationships: an agent-based model. *Social Science Computer Review*, *32*(3), 295-311.

Kanter, R. M. (1977). Some effects of proportions on group life: Skewed sex ratios and responses to token women. *American Journal of Sociology, 82*, 965–990.

King, E.B., Hebl, M.R., George, J.M., & Matusik, S.F. (2009). Understanding tokenism: Antecedents and consequences of a psychological climate of gender inequity. *Journal of Management, 36*, 482-510.

King, E. B., Mohr, J. J., Peddie, C. I., Jones, K. P., & Kendra, M. (2017). Predictors of identity management: An exploratory experience-sampling study of lesbian, gay, and bisexual workers. *Journal of Management*, *43*(2), 476–502.

Klerman, J.A., Daley, K., & Pozniak, A. (2012). *Family and medical leave in 2012: Technical report*. Cambridge, MA: Abt Associates Inc.

Kozlowski, S.W.J., Chao, G.T., Grand, J.A., Braun, M.T., & Kuljanin, G. (2013). Advancing multilevel research design: Capturing the dynamics of emergence. *Organizational Research Methods, 16*(4), 581-615.

Lagos, R., Canessa, E., & Chaigneau, S. E. (2019). Modeling stereotypes and negative self-stereotypes as a function of interactions among groups with power asymmetries. *Journal for the Theory of Social Behaviour*, 1-19.

Lau, D. C., & Murnighan, J. K. (1998). Demographic diversity and faultlines: The compositional dynamics of organizational groups. *Academy of Management Review, 23*(2), 325-340.

Lau, D.C., & Murnighan, J.K. (2005). Interactions within groups and subgroups: The effects of demographic faultlines. *Academy of Management Journal, 48*, 645-659.

Liu, X., Datta, A., Rzadca, K., & Lim, E. P. (2009, November). Stereotrust: A group based personalized trust model. In Proceedings of the 18th ACM conference on Information and knowledge management (pp. 7-16). ACM.

Livingston, R. W., Rosette, A. S., & Washington, E. F. (2012). Can an agentic Black woman get ahead? The impact of race and interpersonal dominance on perceptions of female leaders. *Psychological Science, 23*(4), 354-358.

Lord, R. G., Brown, D. J., Harvey, J. L., & Hall, R. J. (2001). Contextual constraints on prototype generation and their multilevel consequences for leadership perceptions. *The Leadership Quarterly, 12,* 311–338.

Lord, R. G., Foti, R. J., & De Vader, C. L. (1984). A test of leadership categorization theory: Internal structure, information processing, and leadership perceptions. *Organizational Behavior and Human Performance, 34*, 343–378

Macy, M.W., & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology, 28*, 143-166.

Mannix, E., & Neale, M. A. (2005). What Differences Make a Difference? The Promise and Reality of Diverse Teams in Organizations. *Psychological Science in the Public Interest*, *6*(2), 31–55.

Martell, R. F., Lane, D. M., & Emrich, C. (1996). Male-female differences: A computer simulation. *American Psychologist,* 157-158.

Mäs, M., Flache, A., Takács, K., & Jehn, K. A. (2013). In the short term we divide, in the long term we unite: Demographic crisscrossing and the effects of faultlines on subgroup polarization. *Organization Science, 24*(3), 716-736.

Monforti, J. L., & Michelson, M. R. (2008). Diagnosing the leaky pipeline: Continuing barriers to the retention of Latinas and Latinos in political science. *Political Science & Politics, 41*(1), 161-166.

Nye, J. L., & Forsyth, D. R. (1991). The effects of prototype-based biases on leadership appraisals: A test of leadership categorization theory. *Small Group Research, 22*, 360–379.

Offermann, L. R., Thomas, K. R., Lanzo, L. A., & Smith, L. N. (2019). Achieving leadership and success: A 28-year follow-up of college women leaders. *The Leadership Quarterly*, 101345.

Page, S.E. (2018). *The model thinker*. New York, NY: Basic Books.

Pelled, L. H. (1996). Demographic diversity, conflict, and work group outcomes: An intervening process theory. *Organization Science*, *7*(6), 615–631.

Pelled, L.H., Eisenhardt, K.M., & Xin, K.R. (1999). Exploring the black box: An analysis of work group diversity, conflict, and performance. *Administrative Science Quarterly, 44*, 1-28.

Petronio, S. (2002). *Boundaries of privacy: Dialectics of disclosure*. State University of New York Press.

Pettigrew, T.F. (1982). *Prejudice*. Cambridge, MA: Harvard University Press.

Pettigrew, T.F. (1998). Intergroup contact theory. *Annual Review of Psychology, 49*, 65-85.

Quek, B. K., & Ortony, A. (2012). Assessing implicit attitudes: What can be learned from simulations?. *Social cognition*, *30*(5), 610-630.

Ragins, B. R., Singh, R., & Cornwell, J. M. (2007). Making the invisible visible: Fear and disclosure of sexual orientation at work. *Journal of Applied Psychology*, *92*(4), 1103–1118.

Ringelheim, J. (2010). Minority rights in a time of multiculturalism: The evolving scope of the framework convention on the protection of national minorities. *Human Rights Law Review*, *10*, 99-128.

Roberson, Q.M. (2012). Managing diversity. In S.W.J. Kozlowski (Ed.), *The Oxford Handbook of Organizational Psychology, Vol. 2*. (pp. 1011-1033). Oxford, UK: Oxford University Press.

Roberson, Q.M., Ryan, A.M., & Ragins, B.R. (2017). The evolution and future of diversity at work. *Journal of Applied Psychology, 102*, 483-499.

Robison-Cox, J.F., Martell, R.F., Emrich, C.G. (2007). Simulating gender stratification. *Journal of Artificial Societies and Social Simulation, 10*(3), 8.

Rosette, A. S., Koval, C. Z., Ma, A., & Livingston, R. (2016). Race matters for women leaders: Intersectional effects on agentic deficiencies and penalties. *The Leadership Quarterly, 27*(3), 429-445.

Rosette, A. S., Leonardelli, G. J., & Phillips, K. W. (2008). The White standard: Racial bias in leader categorization. *Journal of Applied Psychology*, *93*(4), 758–777.

Rosette, A. S., & Tost, L. P. (2010). Agentic women and communal leadership: How role prescriptions confer advantage to top women leaders. *Journal of Applied Psychology, 95*(2), 221-235.

Rumelhart, D., & McClelland, J.L. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition. (Vol. 1)*. Cambridge, MA: MIT Press.

Sabat, I. E., Lindsey, A. P., King, E. B., Ahmad, A. S., Membere, A., & Arena, D. F. (2017). How prior knowledge of LGB identities alters the effects of workplace disclosure. *Journal of Vocational Behavior*, *103*(Part A), 56–70.

Samuelson, H.L., Levine, B.R., Barth, S.E., Wessel, J.L., & Grand, J.A. (2019). Exploring women's leadership labyrinth: Effects of hiring and developmental opportunities on gender stratification. *The Leadership Quarterly*, *30*(6).

Schelling, T.C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology, 1*, 143-186.

Schröder, T., Hoey, J., & Rogers, K. B. (2016). Modeling dynamic identities and uncertainty in social interactions: Bayesian affect control theory. *American Sociological Review, 81*(4), 828-855.

Scott, K. A., & Brown, D. J. (2006). Female first, leader second? Gender bias in the encoding of leadership behavior. *Organizational Behavior and Human Decision Processes, 101*(2), 230-242.

Silva, C., Carter, N. M., & Beninger, A. (2012). *Good intentions, imperfect executions? Women get fewer "hot jobs" needed to advance*. New York, NY: Catalyst.

SIOP (n.d.). SIOP top 10 workplace trends. Retrieved June 4, 2019 from http://www.siop.org/Business-Resources/Top-10-Workplace-Trends.

Sohn, D., & Geidner, N. (2016). Collective dynamics of the spiral of silence: The role of ego-network size. *International Journal of Public Opinion Research*, *28*(1), 25-45.

Sy, T., Shore, L. M., Strauss, J., Shore, T. H., Tram, S., Whiteley, P., & Ikeda Muromachi, K. (2010). Leadership perceptions as a function of race–occupation fit: The case of Asian Americans. *Journal of Applied Psychology*, *95*(5), 902–919.

Tajfel, H. (1978). *Differentiation between social groups: Studies in the social psychology of intergroup relations* (H. Tajfel (Ed.)). Academic Press.

Talaska, C.A., Fiske, S.T., & Chaiken, S. (2008). Legitimating racial discrimination: Emotions, not beliefs, best predict discrimination in a meta-analysis. *Social Justice Research, 21*, 263-296.

Tsui, A. S., & Gutek, B. A. (1999). *Demographic differences in organizations: Current research and future directions*. Lexington Books/Macmillan.

Turner, J. C., Brown, R. J., & Tajfel, H. (1979). Social comparison and group interest in ingroup favouritism. *European Journal of Social Psychology*, *9*(2), 187–204.

Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory*. Oxford: Basil Blackwell.

Valcour, P. M., & Tolbert, P. (2003). Gender, family and career in the era of boundarylessness: Determinants and effects of intra-and inter-organizational mobility. *International Journal of Human Resource Management, 14*, 768–787.

Vancouver, J.B., & Weinhardt, J.M. (2012). Modeling the mind and the milieu: Computational modeling for micro-level organizational researchers. *Organizational Research Methods, 15*, 602-623.

Wessel, J. L. (2017). The importance of allies and allied organizations: Sexual orientation disclosure and concealment at work. *Journal of Social Issues*, *73*(2), 240–254.

Wilensky, U., & Rand, W. (2015). *An introduction to agent-based modeling: Modeling natural, social, and engineered complex systems with NetLogo*. Cambridge, MA: MIT Press.

Yap, M., & Konrad, A. M. (2009). Gender and racial differentials in promotions: Is there a sticky floor, a mid-level bottleneck, or a glass ceiling? *Relations Industrielles/Industrial Relations, 64*, 593–619.

Figure 1. Neural network model of social categorization based on visual and occupational/status cues

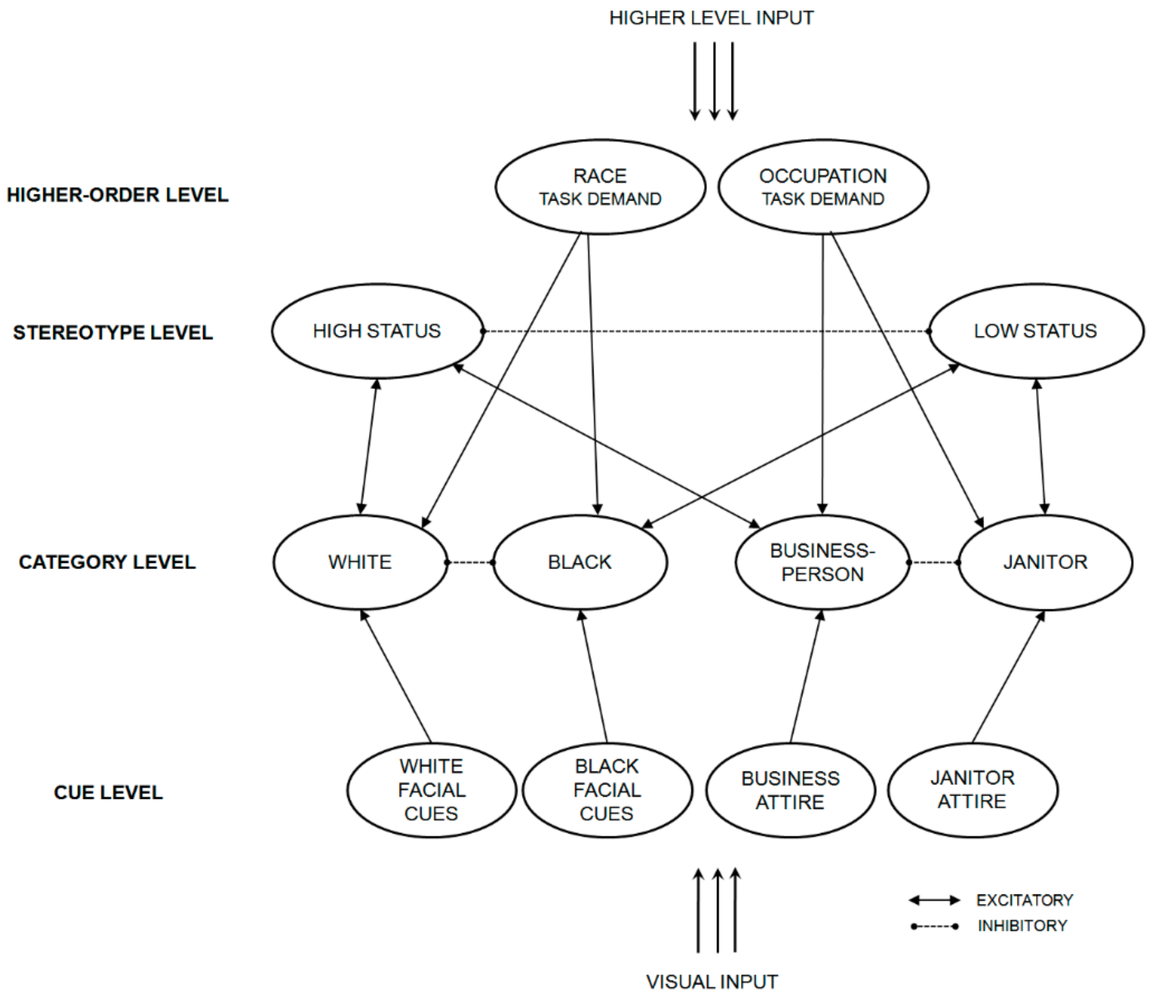

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Table 1. *Reprsentative core concepts, mechanisms, and emergent outcomes in organizational diversity and inclusion research*

Computational model element	Representative diversity & inclusion content	Definition
Core concept	Diversity as factors/categories	Individual-level characteristics capable of producing between-person identity distinctions and result in unique outcomes (Mannix & Neale, 2005; Tsui & Gutek, 1999)
	Compositional diversity	Proportion/variability of specific characteristics within a collective (Tsui & Gutek, 1999)
	Functional/sociocultural diversity	Distribution of task-/job-relevant competencies vs. sociocultural/demographic characteristics in a unit (Pelled, 1996; Pelled, Eisenhardt, & Xin, 1999)
	Surface-level/deep-level diversity	Distribution of easily observable (e.g., demographics, physical features) vs. less easily observable (e.g., values, beliefs, attitudes) attributes in a unit (Harrison, Price, & Bell, 1998; Harrison, Price, Gavin, & Florey, 2002)
	Intersectionality and intrapersonal diversity	Within-person identities that result in unique outcomes vis a vis additive, multiplicative, and/or holistic mechanisms (Crenshaw, 1989)
	Separation, variety, and disparity	Degree to which members differ in their relative standing on an attribute, possess different categories/kinds of attributes, or possess different proportions of a socially valued asset/resource (Harrison & Klein, 2007)
	Faultlines	Degree to which a collective unit can be organized into homogenous subgroups based on members' alignment across multiple attributes (Lau & Murnighan, 1998)
Process mechanisms	Social identification	Individuals seek to enhance self-concept by aligning with valued social groups (Tajfel, 1978)
	Social comparison	Individuals evaluate the attributes and (dis)advantages of social groups (Tajfel, Brown, & Turner, 1979)
	Social categorization	Individuals view self and others in terms of group memberships rather than personal identities (Turner, Hogg, Oakes, Reicher, & Wetherell, 1987)
	Similarity-attraction (homophily)	Individuals are more attracted to others perceived to have similar features, values, beliefs, and attitudes (Berscheid & Walster, 1969; Byrne, 1971)
	Ingroup favoritism	Individuals ascribe relatively positive characteristics to individuals with whom they share a common group identity (Jackson & Hunsberger, 1999)
	Intergroup contact	Interaction among members from different social groups increases likelihood of viewing diverse others in terms of personal vs. group identities (Blau, 1977; Pettigrew, 1982)
	Social competition	Competition over scarce resources perpetuates in-group/out-group distinctions (Blalock, 1967; Bonacich, 1972)
Emergent/Dynamic Outcomes	Stereotypes/stigma	Generalized (and often negative) attributions or beliefs about the personal attributes associated with a group and its members (Hilton & von Hippel, 1996)

Prejudice	Adverse attitudes, negative judgments, or hostile evaluations directed towards one or more individuals because of their group membership (Allport, 1954)
Discrimination	Enactment of harmful or detrimental behaviors toward a group or individuals belonging to that group (Al Ramiah, Hewston, Dovidio, & Penner, 2010).
Segregation/stratification	Clustering of individuals in distinguishable strata, areas, locations, categories, etc. based on group identification or affiliation (Allport, 1954; Schelling, 1971)

Table 2. *Representative examples of computational models relevant to organizational diversity and inclusion*

Model Type	Level	Common themes	Source
Neural Network	Individual	Origin of attitudes/stereotypes	Ehret, Monroe, & Read (2015) Freeman & Ambady (2011) Freeman, Penner, Saperstein, Scheutz, & Ambady (2011) Quek & Ortony (2012)
Agent-Based	Individual	Origin of attitudes/stereotypes Consequences of stereotypes	Grand (2017) Lagos, Canessa, & Chaigneau (2019) Liu, Datta, Rzadca, & Lim (2009) Schroder, Hoey, & Rogers (2016)
	Group	Opinion formation/spread Group genesis/intergroup relations Faultlines/composition	Alvarez-Galvez (2016) Flache & Mäs (2008a) Flache & Mäs (2008b) Flache & Macy (2011) Gawronski, Nawojczyk, & Kulakowski (2014) Gray, Rand, Ert, Lewis, Hershman, & Norton (2014) Hong & Page (2004) Joseph, Morgan, Martin, & Carley (2014) Mäs, Flache, Takács, & Jehn (2013) Sohn & Geidner (2016)
	Organizational	Organizational segregation & stratification	Abdou & Gilbert (2009) Martell, Lane, & Emrich (1996) Robison-Cox, Martell, & Emrich (2007) Samuelson, Levine, Barth, Wessel, & Grand (2019)

Table 3

Pseudocode for Flache & Mäs (2008b) computational model of team faultlines

Step	Action
1	Initialize iteration timer $t = 0$
2	Create team with N members
3	Assign D demographic attributes to each team member such that aggregate team faultline strength = f
4	Randomly assign K work-related opinions to each team member
5	Compute initial interpersonal influence weights (w) between all members
6	Set counter to $m = 0$
7	Randomly select one team member i and randomly do ONE of the following: A. Update all K work-related opinions for member i B. Update all interpersonal influence weights w for member i
8	Increment counter to $m = m + 1$
9	If $m < N$, return to Step 7
10	Compute aggregate team outcomes for iteration t
11	Increment iteration timer to $t = t + 1$
12	If $t < t_{stop}$, return to Step 6
13	End

Note. Flache and Mäs (2008b) do not provide an overview of the pseudocode for their model. The order and description of steps is based on our interpretation of the model description provided in the original publication. t = iteration number; t_{stop} = iteration number at which to stop simulation

Table 4
Pseudocode for Samuelson et al. (2019) computational model of gender stratification in organizational leadership

Step	Action
1	Initialize time clock $t = 0$
2	Create organizational structure and populate with initial employees
3	Increment time clock $t = t + 1$
4	Assign developmental opportunities and determine which employees take assigned opportunities based on risk-taking propensity
5	Calculate base performance score, add opportunity values to employees' performance scores, accumulate total performance scores
6	If remainder of $t/12 \neq 0$, return to Step 3
7	Assign career delays, deduct performance rounds from delay takers, and assign turnover to specified percentage of delay takers
8	Update employee tenure at level and age, calculate likelihood of turning over due to level tenure, age, and tokenism (for women only)
9	Invoke voluntary turnover based on total turnover likelihood
10	Fill specified percentage of open positions with external hires
11	Promote employees into remaining open positions
12	Fill open positions in lowest level of organization with external hires
13	If the number of original employees is greater than 0, return to Step 3
14	End

Note. T = time period.