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Innovation Teams and Organizational Creativity: Reasoning with Computational Simulations

Abstract A computational social simulation encourages systematic reasoning about the management of innovation teams and organizational creativity. This article draws upon historical literature to identify a potential dilemma faced by business organizations: Is it better to promote creative behavior across a whole organization or focus on the development of small and highly creative teams? We formulate the dilemma from the literature on organizational creativity, and explore it using a multi-agent simulation. Our study models creative behavior abstractly, as the ability to introduce novelty. By varying the scale and scope of non-conformist behavior in the simulation, our research supports the systematic study of the *breadth vs. depth* dilemma. The results of this study invite an informed examination of strategies to sustain innovation based on the introduction of either a small number of significantly novel ideas, or a large number of novel but more familiar ideas. Results from this study on change agency also indicate that there is a possible trade-off between a highly creative team and its creative efficiency, drawing attention to the importance of a creative critical mass in an organization. We also discuss the implications of these results and our research approach.

Keywords
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1 Frederic D. Randall, "Stimulate Your Executives to Think Creatively," *Harvard Business Review* 33, no. 4 (1955): 128.

2 Andrew Hargadon, "Creativity That Works," in *Handbook of Organizational Creativity*, ed. Jing Zhou and Christina E. Shalley (London: Psychology Press, 2007), 340.

3 Michael D. Mumford, ed., *Handbook of Organizational Creativity* (London: Academic Press, 2012), 708.

4 Jing Zhou and Christina E. Shalley, eds., *Handbook of Organizational Creativity* (London: Psychology Press, 2007), 352.

5 Christina E. Shalley and Lucy L. Gilson, "What Leaders Need to Know: A Review of Social and Contextual Factors that Can Foster or Hinder Creativity," *The Leadership Quarterly* 15, no. 1 (2004): 39, DOI: https://doi.org/10.1016/j.leaqua.2003.12.004.

6 Ruth Richards, ed., *Everyday Creativity and New Views of Human Nature: Psychological, Social, and Spiritual Perspectives* (Washington, DC: American Psychological Association, 2007), 25.

7 Karan Girotra, Christian Terwiesch, and Karl T. Ulrich, "Idea Generation and the Quality of the Best Idea," *Management Science* 56, no. 4 (2010): 593, DOI: https://doi.org/10.1287/mnsc.1090.1144.

8 Randall, "Stimulate Your Executives to Think Creatively," 128.

9 Nigel Gilbert, *Agent-Based Models*, No. 153 (Los Angeles: Sage, 2008), 2.

Introduction

Scholars have noted the strategic role that creativity plays in business for more than six decades. As early as the 1950s, specialized articles recommended that business leaders "work hard at the task of maintaining a stimulating atmosphere for creative thinking."[1] Today, evidence-based recommendations to foster creative organizational climates include the recognition that "the challenge to creativity is understanding when and where to be creative, and the set of practices that support practical creativity entail strategically allocating your creative efforts."[2] Organizational creativity is highly complex because "creativity is complex, leading creative efforts is complex, and planning for creativity is also complex. Thus we are left with an array of interrelated factors affecting creative efforts which are complicated to articulate, and even more complicated to implement successfully."[3] A fundamental question related to this complexity is the tension between cultivating creativity widely across the organization or focusing on augmenting the creativity of a few specialists.[4] As with other dichotomies in the management of competing demands of creative and routine work, a critical leadership function is to ensure that support and resources are available for creative work, whilst "an overabundance may stifle their creativity."[5]

Businesses need leadership strategies to better support the kind of idea generation that leads to radical or disruptive change or innovation. On the one hand, creative capacities are universal and essential for "our health and well-being, offering richness and alternatives in what we do, and helping us move further in our creative and personal development."[6] In that sense, organizations could seek to promote the creative capacities of all their employees. However, considering the intricacies involved in evaluating new ideas, and the journey between idea and implementation, a substantial growth in new individual initiatives may lead to unfeasible and uncertain results at the organizational level. In the context of innovation, "an organization would prefer ninety-nine bad ideas and one outstanding idea to one hundred merely good ideas."[7] Some have characterized the question between exploitation and exploration as the *dilemma of management*: "great profits may result from increased efficiency, and equally great profits may result from creativity and inventiveness. Yet the means by which the two are stimulated are not necessarily compatible."[8]

In order to jump-start disruptive change, there are two possible types of strategies for organizational creativity: allocate resources to support new initiatives across the entire organization (*breadth-first*), or sacrifice scope and concentrate on specialized units of change agency (*depth-first*). Leaders face such breadth-first vs. depth-first dilemmas when it comes to facilitating change initiatives in their organizations. These strategies may lead to different types of outcomes. However, we do not sufficiently understand the effects of implementing the strategies and hence there is no clear guidance on how to resolve the breadth vs. depth dilemma.

In this article, we present a computational social simulation as a method for systematic inquiry into change agency principles in business organizations. We use agent-based simulation as a lens through which to consider key ideas related to organizational creativity. This approach enables us to define and implement models representing the characteristics and behavior of individual agents, and analyze multiple scales of interaction, including the emergence of macro or societal structures from aggregate, decentralized, individual action.[9]

In the second section of the article, we review the literature on organizational creativity, focusing on the breadth-depth dilemma as explained above, and previous studies of social creativity using computational social simulations. In section three, we describe a simulation model built to examine the effects of disruptive individuals in a societal group. Section four contains a summary of the results from analyzing a range of parameters in the model. Section five closes the article with a discussion around the implications of this model, and the future of computational social simulation as part of the research toolbox in the management of creativity and innovation.

Background

Sixty years ago, strategies to build creative organizations included the goal to increase "the creativeness of five hundred individuals each by, say, one percent."[10] Behind the idea of marginal increments across an entire organization was the notion that direct expertise is a pivotal to triggering change – "those who are to do the work are likely to have valuable ideas as to how it might be done."[11] A key assumption behind such advice is that nearly everyone is creative to a certain extent, yet people who "display lesser talents in this area are trapped by a system which serves to suppress even the small degree of creativity which they may possess."[12]

Six decades later, the specialized press continues to present general recommendations such as warning against "the hazards of not distributing creative responsibilities across the organization."[13] Today many experts subscribe to the tenet that most people are born creative, and recommend that employees be supported in the process of rediscovering their creative confidence – the disposition to generate and try new ideas.[14] However, the notion that all people are creative is still controversial one,[15] and some are not convinced that it is true. The capacity to hold contradictory beliefs and the gap between beliefs and behavior can also be determinant. For example, while most teachers agree that creativity is universal, they also believe that only a small portion (five to ten percent) of their students display creative behavior.[16]

There are different ways in which the premise of universal creativity is challenged. Mihaly Csikszentmihalyi and Robert Epstein debated the extent to which "reality puts boundaries on what is needed and what is useful," arguing that if an organization tries to make "their twenty-five thousand engineers more creative, what happens? Nothing, because … you get lots of new ideas, but no one knows which are good and which are bad."[17] It may be that organizations do have systemic limits to creative behavior, but we need more evidence – beyond thought experiments and persuasive inferences – to examine such dynamics.

In practice, most idea generation or ideation techniques rest on two key assumptions: first, that all individuals have creative capacity; and second, that specific techniques can transform that potential into action. Alex Osborn's *Applied Imagination* marked the beginning of the corporate use of brainstorming, claiming that by enacting a few rules of engagement "the average person can think up twice as many ideas."[18] Today, ideation techniques such as brainstorming are commonly used tools in business, even though researchers continue to analyze and debate their effectiveness.[19]

These days, many continue to ascribe creative abilities to an elite few. A recent study inspecting the genetic roots of creativity and psychosis defined creative people *a priori* as "those belonging to the national artistic societies of actors, dancers, musicians, visual artists, and writers,"[20] excluding all other professions. That a population can be divided into a non-creative majority and a creative elite is a simple but consequential assumption, often taken at face value.[21] Yet business scholars have long warned against limiting creativity to "a very few in key decision-making posts."[22]

In sum, scholars as well as practitioners debate whether organizations should task everyone with generating disruptive ideas, or rather focus on a specialized

10 Randall, "Stimulate Your Executives to Think Creatively," 121.

11 Ibid., 125.

12 Ibid., 121.

13 Teresa A. Amabile and Mukti Khaire, "Creativity and the Role of the Leader," *Harvard Business Review* 86, no. 10 (2008): 102. also available at https://hbr.org/2008/10/creativity-and-the-role-of-the-leader.

14 Tom Kelley and David Kelley, "Reclaim Your Creative Confidence," *Harvard Business Review* 90, no. 12 (2012): 115–18, also available at https://hbr.org/2012/12/reclaim-your-creative-confidence.

15 Elizabeth B.-N. Sanders and Pieter Jan Stappers, *Convivial Design Toolbox: Generative Research for the Front End of* Design (Amsterdam: BIS Publishers, 2012), 8.

16 Dina Aish, *Teachers' Beliefs about Creativity in the Elementary Classroom* (Malibu, CA.: Pepperdine University, 2014), 81.

17 Mihaly Csikszentmihalyi and Robert Epstein, "A Creative Dialogue," *Psychology Today*, last modified June 9, 2016, https://www.psychologytoday.com/articles/199907/creative-dialogue.

18 Alex F. Osborn, *Applied Imagination: Principles and Procedures of Creative Thinking* (New York: Scribner, 1953), 229.

19 Robert I. Sutton and Andrew Hargadon, "Brainstorming Groups in Context: Effectiveness in a Product Design Firm," *Administrative Science Quarterly* 41, no. 4 (1996): 715, DOI: https://doi.org/10.2307/2393872.

20 Robert A. Power et al., "Polygenic Risk Scores for Schizophrenia and Bipolar Disorder Predict Creativity," *Nature Neuroscience* 18, no. 7 (2015): 954, DOI: https://doi.org/10.1038/nn.4040.

21 Jamie Peck, "Struggling with the Creative Class," *International Journal of Urban and Regional Research* 29, no. 4 (2005): 766, DOI: https://doi.org/10.1111/j.1468-2427.2005.00620.x.

22 Randall, "Stimulate Your Executives to Think Creatively," 128.

23 Gilbert, *Agent-Based Models*, 2.

24 Ibid., 4.

25 Robert M. Axelrod, *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration* (Princeton: Princeton University Press, 1997), 151.

26 Ibid.

27 Ibid., 168.

28 Christopher Watts and Nigel Gilbert, *Simulating Innovation: Computer-Based Tools for Rethinking Innovation* (Cheltenham, UK: Edward Elgar Publishing, 2014).

29 Jesse Olson, Jonathan Cagan, and Kenneth Kotovsky, "Unlocking Organizational Potential: A Computational Platform for Investigating Structural Interdependence in Design," *Journal of Mechanical Design* 131, no. 3 (2009): 031001-1–031001-13, DOI: https://doi.org/10.1115/1.3066501.

30 Ibid.

31 Christopher McComb, Jonathan Cagan, and Kenneth Kotovsky, "Lifting the Veil: Drawing Insights about Design Teams from a Cognitively-Inspired Computational Model," *Design Studies* 40, (September, 2015): 119–42, DOI: https://doi.org/10.1016/j.destud.2015.06.005.

32 Ibid.

33 Christopher McComb, Jonathan Cagan, and Kenneth Kotovsky, "Optimizing Design Teams Based on Problem Properties: Computational Team Simulations and an Applied Empirical Test," *Journal of Mechanical Design* 139, no. 4 (2017): 041101-1–041101-12, DOI: https://doi.org/10.1115/1.4035793.

34 Vishal Singh, Andy Dong, and John S. Gero, "Computational Studies to Understand the Role of Social Learning in Team Familiarity and Its Effects on Team Performance," *CoDesign* 8, no. 1 (2012): 25–41, DOI: https://doi.org/10.1080/15710882.2011.633088.

35 Vishal Singh, Andy Dong, and John S. Gero, "Social Learning in Design Teams: The Importance of Direct and Indirect Communications," *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM* 27, no. 2 (2013): 167–82, DOI: https://doi.org/10.1017/S0890060413000061.

group of creative types. There seem to be compelling arguments for both scenarios, but these may reflect more the ideological stance of their authors than any conclusion supported by evidence. To move forward, we must better understand the type of change caused by breadth-first and depth-first approaches, and the leadership strategies to deploy across different situations and scenarios. One way to advance the study of creativity in organizations is to reconsider first principles, and to examine key components and dynamics of the complex themes involved. This going back to basics requires a degree of simplification and demands precision and clarity. Computational simulations can assist in the systematic study of elementary processes of organizational creativity. In this article, we adopt an agent-based modeling approach to examine these issues and support our reasoning about how creativity emerges from the micro-macro interactions in a group. Rather than replicate a specific case, the role of these simulations here is to inform discussion and assist in the planning of future work, particularly future experimental studies that include both computational simulation and analysis of real teams.

Computational Social Simulation

We address the breadth-depth dilemma here via a computational simulation as a means to understand the effects of incentivizing initiatives of change in the organization. Agent-based modeling is "a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment."[23] Crucially, these models are *analogical* in nature – they are built to understand the social world by "drawing an analogy between some better understood phenomenon and the target."[24] The model we present here extends work on agent-based simulation that offered "a new way of looking at the dynamic process of social influence."[25] Agent-based simulation (ABS) is suitable for the study of individual and group behavior because in systems of multiple interacting agents, emergent outcomes grow, enabling experimentation with the model's variables and informed reasoning about the target system. These models are not predictive; instead, they are meant "to show the consequences of a few simple assumptions" about group change.[26] This function is particularly useful when "intuition is not a very good guide for predicting what even a simple dynamic model will produce."[27]

In recent years, agent-based simulation has been used to examine challenging questions of creativity and innovation.[28] Researchers have used a range of computational agents that model design performance to represent complex design tasks where the output is contrasted against data from real cases.[29] The team dimension in such work includes the exchange of information toward a shared goal, where every task variable is controlled individually by each agent.[30] An alternate approach consists of configuring software agents to model results from laboratory studies of simplified optimization tasks.[31] Researchers in this case have assessed team performance by identifying individual agent characteristics that determine the frequency of sharing and building upon partial solutions in a group of agents.[32] More recently, that model has been used to compare the effects of collaboration in teams of novice designers and software agents suggesting that lower interaction frequencies are preferable for simplified configuration tasks.[33] Agent simulations have also been applied to the study of social learning in groups, showing that different types of direct and indirect interaction may affect the performance of design teams – particularly when team familiarity is high and task complexity is low[34] – and as a function of team structure.[35]

The model we present shifts the focus from modeling design behavior in a group of computational agents to modeling the role of agent teams in introducing change across an organization. In this article, we use the term "innovation team" to refer broadly to agents in an organization tasked with introducing change initiatives. This model belongs to a class of agent-based simulations used to gain qualitative understanding of human and social behavior rather than to replicate data from case studies or laboratory studies. Such small-scale models are advantageous because they are easily communicated, replicated, and extended in comparison to agent models that are "burdened by high model complexity."[36] The model extends the Axelrod model of culture dissemination, which is a type of two-dimensional cellular automata where a population of agents interacts in a shared environment guided by simple representations and behaviors – a full description of the modeling assumptions and the definition of the variables is given elsewhere.[37] In that model, agents communicate opinions or ideas, which are encoded as chains of numerical values; specifically, ideas are collections of features with traits. To an extent, features in this model represent the size of the problem space, and traits indicate the size of the solution space. Thus, the number of design features would be high when modeling groups that tackle a problem where many decisions are negotiated, whereas in model groups where only a few parameters were discussed, the number of design features would be low. When each parameter has only a few possible values, the number of traits in the model remains low; when each parameter has a vast number of possible values, then the number of traits in the model is large. Using car design to illustrate these notions, design features such as "sunroof" have binary or yes/no values or traits, whilst design features such as "number of seats" may vary from two to seven, and design features such as "exterior color" usually have a large number of traits.

The core agent function in the Axelrod model is the local and stochastic exchange of ideas. These local interactions create emergent outcomes that help the researchers better understand the modeling assumptions and the type of processes that are possible in such systems. Caution needs to be exercised to avoid making unsupported claims; the value of these models is to support reasoning, to assess first principles, and to frame our intuitions and arguments about change initiatives in organizations. Notice that the Axelrod model discussed here is domain and task independent.

In the initial state of the Axelrod model, agents are instantiated with a unique location in a two-dimensional space and with random values assigned for ideas. A torus grid and neighborhood type "von Neumann" (adjacent neighbors to the north, south, east and west) are both customary in these models. At every simulation step, each agent becomes active and adopts a feature from one of its neighbors. Over time, from these local exchanges, the population reaches global consensus on an idea collectively built by all agents through their local value exchanges. A winning idea in this type of models becomes dominant by the aggregate effect of agent interactions without any centralized control, and since they are domain and task independent, there is no need for an objective function to guide the search. Experimentation is possible with the factors that lead to convergent outcomes, for example the effects of limiting local exchanges to agent compatibility.[38] Even if the rate of convergence and the shape of the emergent patterns in these stochastic models can vary, the general trend to ergodicity is unaffected by the number of agents, the type of neighborhoods, or their number of features and traits.

Figure 1 shows a visual representation of the original Axelrod model in two frames: the left side shows a population of agents in a two-dimensional grid, or lattice, of 10 x 10 agents; to the right, a single agent is magnified and depicted via six concentric circles color-coded according to numerical values mapped to a color space. Agent #23 with values {0,4,2,4,0,7} is shown in Figure 1. When agents interact, these rings change color as a function of the values exchanged with

36 McComb, Kagan and Kotovsky, "Lifting the Veil," 120.

37 Robert Axelrod, "The Dissemination of Culture: A Model with Local Convergence and Global Polarization," ***Journal of Conflict Resolution*** **41, no. 2 (1997): 208, DOI: https://doi.org/10.1177/0022002797041002001.**

38 Ibid., 217.

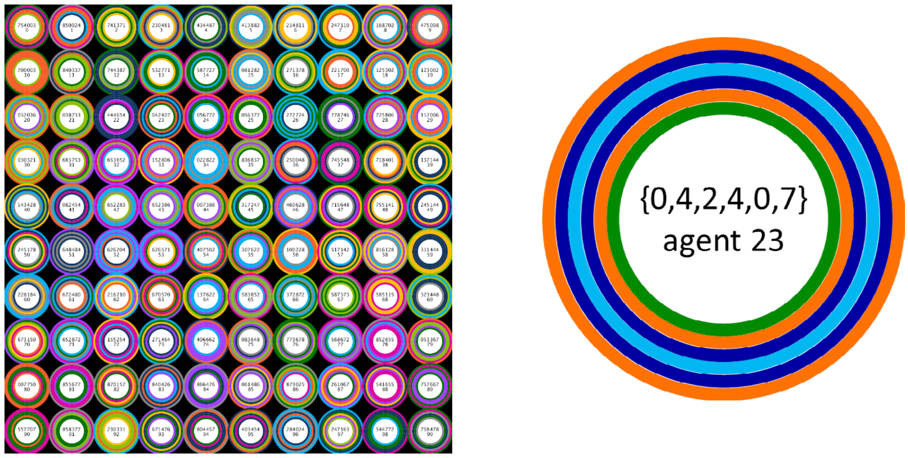


Figure 1 One way to represent agents in the Axelrod model of culture dissemination: concentric circles using color to visualize the string of values adopted by every individual in the grid. Copyright © 2018 Ricardo Sosa and Andy Connor.

neighboring agents.[39] As far as we know, this is an original and visually intuitive way of representing agent features and traits in the Axelrod model. This highly abstract model simplifies complex systems of organizational creativity such as ideation sessions, open innovation programs, and idea banks to a level that enables full specificity and advanced clarity of thinking.

Using an Axelrod model to understand group convergence can be important when reasoning about creativity because groups who agree upon criteria such as novelty and usefulness consider innovative ideas creative. Other researchers have similarly applied the Axelrod model to study themes related to creativity and innovation.[40] We suggest here that for these systems to be relevant as reasoning aids in the study of creativity, they need to support divergence. One way to capture divergence in these models is to include an agent behavior inspired by the human bias to avoid monotonous, homogeneous stimuli. With a mechanism of *dissent*, agents are allowed to introduce a new value with the intention to trigger group change.

We introduce here two variations to the original Axelrod model in order to study principles of change agency in organizations: first, dissent is defined as an individual behavior that attempts to generate a new, random value in the presence of local monotony. This is a behavior observed in social[41] and evolutionary systems.[42] The probability of dissent in social and biological systems is low.[43] As a baseline, the probability of generating a dissent value in this model is one one-hundredth of a percent (0.01%) when an agent perceives full convergence in his or her neighboring agents – in other words, when all local interactions repeatedly return the same values. The link between such individual dissent and the group's state is based on the observation that change agency which leads to creative behavior is associated with traits such as openness and novelty seeking.[44] Research has shown that introducing change agents in social simulations generates waves of gradual convergence and punctuated divergence in the agent groups.[45]

Second, we manipulate the scope and degree of dissent in a group. We define scope of dissent (D_S) as the ratio of agents in the simulation model who engage in dissent by generating new values when sensing local convergence as described above. The range of values to examine in a group of size N goes from $D_S = 1/N$ to $D_S = N$: in other words, from the point where only a single agent in the simulation displays dissent to the other extreme where all agents have access to the role of dissent. Models with low D_S values represent organizations where a specialized elite – or even a single person – is tasked with generating creative initiatives, while models with high D_S values represent organizations that aim to include many people – possibly the entire group – in creative problem solving.

Degree of dissent (D_D) consists of the level of change that dissenting agents

39 A video animation showing this process simulated over time is available at https://youtu.be/HxEGbQ5QoaM.

40 Watts and Gilbert, *Simulating Innovation*, 172.

41 Cass R. Sunstein, *Why Societies Need Dissent* (Cambridge: Harvard University Press, 2005).

42 Andreas Wagner, *Arrival of the Fittest: Solving Evolution's Greatest Puzzle* (New York: Penguin, 2014).

43 Ibid., 23.

44 Jason Meneely and Portillo Margaret, "The Adaptable Mind in Design: Relating Personality, Cognitive Style, and Creative Performance," *Creativity Research Journal* 17, no. 2-3 (2005): 155–66, DOI: https://doi.org/10.1080/10400419.2005.9651476.

45 Ricardo Sosa and John S. Gero, "A Computational Study of Creativity in Design: The Role of Society," *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM* 19, no. 4 (2005): 241, DOI: https://doi.org/10.1017/S089006040505016X.

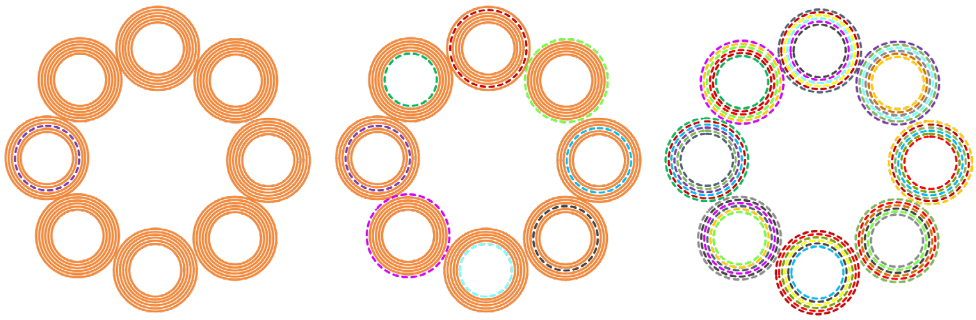


Figure 2 Scope and degree of dissent. Copyright © 2018 Ricardo Sosa and Andy Connor.

have access to. The range of parameters in a model where agents exchange f features goes from $D_D = 1/f$ to $D_D = f$ – from agents who dissent by changing only one design feature at a time to models where change agents can generate novelty across all design features. Models with low D_D values represent situations where agents propose marginal or incremental changes, while models with high D_D values stand for situations where new initiatives are radical or disruptive. Introducing degree of dissent in the model enables direct experimentation of the effects of breadth-depth strategies on radical versus incremental innovation beyond assumptions related to structural types.[46] Figure 2 illustrates the concepts of scope and degree of dissent with eight agents in a circular arrangement. The first case (left) shows a group with low scope and low degree of dissent – only one individual presents a differentiated value in one of the design features being discussed; the second case (center) shows a group with high scope but low degree of dissent – all individuals present one differentiated idea; and the third case (right) shows a group with high scope and high degree of dissent – all individuals introducing dissimilar ideas across all the design features under discussion.

The scope of dissent defines the number of agents in the simulation capable of introducing novelty, whereas the degree of dissent defines the number of design features that any given agent can modify. The introduction of dissent in the Axelrod model – and in particular the possibility of manipulating its scope and degree – helps researchers tackle the breadth-depth dilemma by enabling them to examine the effects of increasing "the creativeness of five-hundred individuals each by, say, 1%," as Frederic Randall imagined over sixty years ago.[47] This simulation model represents Randall's ideal when the scope of dissent is broad and the degree of dissent is low. By systematically varying both the scope and degree of dissent, it becomes possible to explore the implications of varying compositions of creativity in innovation teams.

These model variables allow researchers to experiment with factors that shape "creative group capacity," defined here by the likelihood a population has of exhibiting cycles of divergence and convergence that transform new ideas (innovations) into dominant ideas (traditions).[48] In this model, a single agent can trigger a global change – albeit with a very low probability – when the group unanimously adopts a new value as the result of aggregate local exchanges. For this reason, some might consider certain model conditions more conducive to change agency than others. In order to systematically compare effects in stochastic models, simulations are run over extended periods of time and behavior is averaged across many cases. However, beyond average cases, we suggest that meaningful comparisons across model conditions include extreme values such as the top decile, since in the study

46 John E. Ettlie, William P. Bridges, and Robert D. O'Keefe, "Organization Strategy and Structural Differences for Radical versus Incremental Innovation," *Management Science* 30, no. 6 (1984): 682–95, DOI: https://doi.org/10.1287/mnsc.30.6.682.

47 Randall, "Stimulate Your Executives to Think Creatively," 121.

48 Everett M. Rogers, *Diffusion of Innovations*, 4th ed. (New York: Free Press, 2003).

of creativity and innovation "the extremes are what matter, not the average or the norm."[49]

49 Girotra et al., "Idea Generation and the Quality of the Best Idea," 1.

50 Ricardo Sosa and John S. Gero, "Multi-dimensional Creativity: A Computational Perspective," *International Journal of Design Creativity and Innovation* 4, no. 1 (2016): 30, DOI: https://doi.org/10.1080/21650349.2015.1026941.

51 Axelrod, "The Dissemination of Culture," 209.

52 Robert Axtell, Robert Axelrod, Joshua M. Epstein, and Michael D. Cohen. "Aligning Simulation Models: A Case Study and Results," *Computational and Mathematical Organization Theory* 1, no. 2 (1996): 126, DOI: https://doi.org/10.1007/BF01299065.

Experimental Approach

The purpose of the experiments we present here is to explore the impact on change agency by manipulating the source of new ideas. In particular, our research explores the continuum of possibilities between the extremes of lesser and greater creative agency in an innovation team and the increase in creative capacities of team members – which we understand here as the capacity to introduce change initiatives that lead to organizational change. As a result, we vary the two parameters we defined earlier: the scope of dissent, D_S, and degree of dissent, D_D. This variation essentially provides insight into the effects of dissent in a group, and the effects of introducing marginal or radical ideas into a creative team. Following a multi-dimensional modeling approach to computational creativity, D_S in this study is a group property and D_D corresponds to an individual feature.[50]

A parameter sweep is carried out in these models by making sure that all system conditions are kept constant – including random seed generators – and executing a number of cases by manipulating the scope of dissent and gradually moving along a specified range of values. This is repeated for different degrees of dissent to produce a number of outcomes that can be compared and contrasted. A single dependent variable is used here, called "group changes" (Δg) – the number of collective changes of dominant values in a population. When a change agent introduces a new value, and all the agents in the simulation adopt it to replace a previously dominant value, a group change is registered. The sum of Δg is the key output from these experiments.

Each simulation utilizes a model with one hundred agents in a 10 × 10 grid, with agents having six features and ten traits ($N = 100, f = 6, t = 10$). As Axelrod specified,[51] each of the six features associated with each agent may take one of ten values. This focus on small groups seeks to increase clarity and support future extensions with more complex agent behaviors. Using this model, we explore a total of six hundred cases, where each case consists of a unique characterization of dissent. Each unique characterization consists of a unique number of agents able to cause dissent ($D_S = 1$ to $D_S = 100$, since $N = 100$) and the extent to which dissent can impact the features of the agent, from one to all features ($D_D = 1$ to $D_D = 6$, since $f = 6$). For each case, 10^3 simulations are performed for a total of 10^4 simulation steps, following recommended model docking practices.[52] This enables us to determine the average outcome for each case with statistical confidence.

Results

The results we present here are a representative sample of the outcomes from the experimental cases outlined in the previous section. For brevity, we present the results showing the impact of varying the scope of dissent by just three different degrees of dissent. Figure 3 shows the results of varying the scope (D_S) and degree (D_D) of dissent in the extended Axelrod model for the case when the degree of dissent is at its smallest. When $D_D = 1$, the degree of dissent is limited to the change of a single design feature. This represents the case where the degree of change agency exercised by each individual is increased by a small amount. Changing the scope of dissent allows the impact of that increase in change agency to be extended across the whole team as the value of D_S changes from 1 to 100.

Figure 3 plots the average number of group changes (Δg) as columns ordered by $D_S = 1$ to $D_S = 100$. When groups have only one agent able to create dissent, the

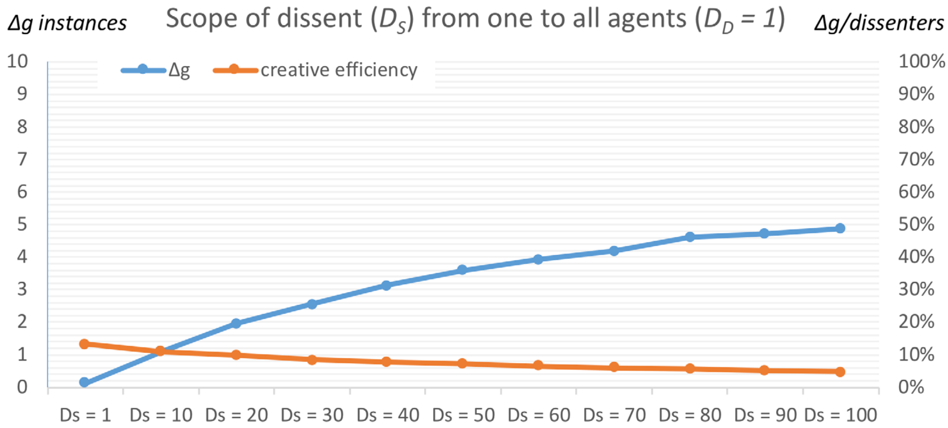


Figure 3 Parameter sweep of scope of dissent (D_S) from one to all one hundred agents (degree of dissent $D_D = 1$ of 6 features). Copyright © 2018 Ricardo Sosa and Andy Connor.

average Δg value is 0.132, a number that increases to 1.104 when one tenth of the agent group has access to dissent and reaching a maximum value of 4.876 when all agents in the simulation create dissent. Figure 3 also includes a trend line in the secondary axis that plots what we define as the group's "creative efficiency,"—the average Δg value divided by the number of dissenting agents, essential D_S. In this sense, creative efficiency is a measure of the team "cost" to stimulate a group change. If a large number of dissenting agents only produces a small number of group changes, then this is less efficient than when a small number of agents produces a large number of group changes. This captures the idea that increasing the creative capacity of a group has the obvious consequence of increasing the average number of group changes. However, it also suggests that such growth need not be linear—it may also lead to a marked decrease in the creative value that individual change agents bring to the group.

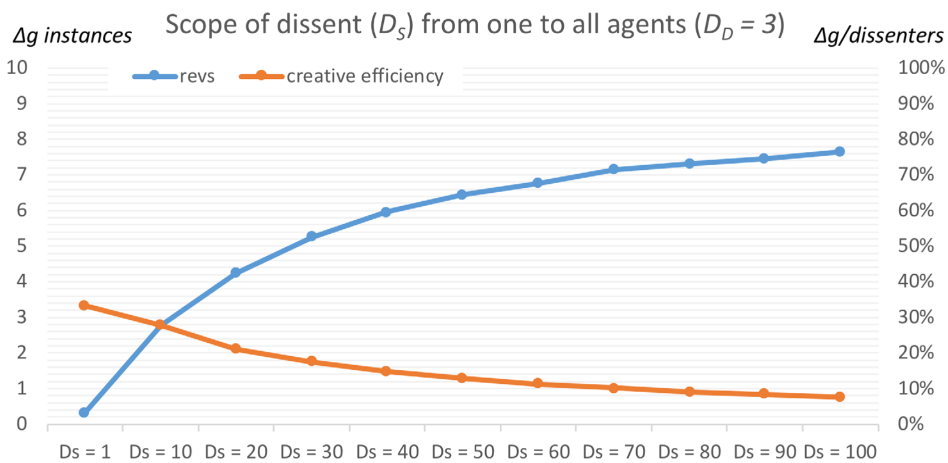
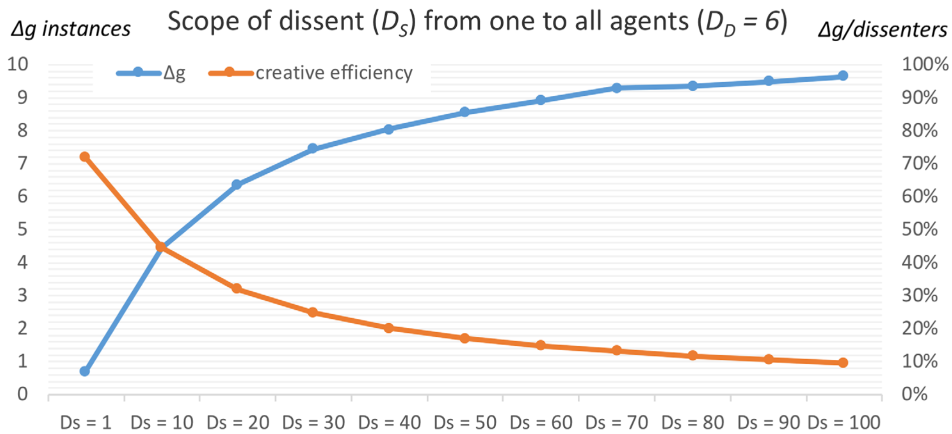


Figure 4 Parameter sweep of scope of dissent (D_S) from one to all one hundred agents (degree of dissent $D_D = 3$ of 6 features). Copyright © 2018 Ricardo Sosa and Andy Connor.

Figure 4 shows the results of varying the scope (D_S) of dissent in the extended Axelrod model for cases where the degree of dissent is moderate ($D_D = 3$)—in other words, when dissent is limited to half of the design features available to each agent. When the degree of dissent is moderate, and only one agent in the simulation creates dissent, an average Δg of 0.334 is produced, increasing to $\Delta g = 2.785$ when one tenth of the agents can dissent, then gradually slowing down to $\Delta g = 7.653$ when all of the agents in the simulation can create dissent. This shows a considerable increase in the number of group changes as the degree of dissent is increased.

Finally, Figure 5 shows the results of varying the scope (D_S) of dissent in the extended Axelrod model for cases where the degree of dissent is radical ($D_D = 6$)—in

Figure 5 Parameter sweep of scope of dissent (D_S) from one to all one hundred agents (degree of dissent $D_D = 6$ of 6 features). Copyright © 2018 Ricardo Sosa and Andy Connor.



other words, cases when the degree of dissent is such that an agent can change all of the design features. When the degree of dissent is extreme and only one agent in the simulation creates dissent, the average Δg value is 0.717, increasing to $\Delta g = 4.451$ when one tenth of the agents has access to dissent. This growth continues but slows down up to a total of $\Delta g = 9.646$ when all agents in the simulation are able to introduce new ideas.

A comparison of the average number of group changes (Δg) shows an important interaction between scope and degree of dissent: when new initiatives are disruptive ($D_D = 6$), having one third of the agents in the simulation creating dissent produces around seven and a half group changes, a similar range to simulations where all agents can generate moderate changes ($D_D = 3$). In groups where all agents generate minimal changes ($D_D = 1$), the group produces around five group changes, equivalent to that of only one tenth of agents in disruptive groups. What remains constant across conditions is that any increase in the scope of dissent is likely to increase the creative capacity of the group. However, this is most significant when the scope of dissent is increased from a low value and lower gains are observed at higher values of D_S.

A comparison of efficiency rates between high, medium, and low D_D values shows that the efficiency of the first few change agents (low D_S values) scales uniformly with their degree of dissent (from 72% to 33% and 13%, respectively). This means that when dissenting agents are a minority, introducing bolder new ideas makes group changes more likely. However, as the number of dissenting agents continues to increase in a group, less radical dissent is proportionally more efficient than more radical dissent.

In all three cases analyzed here, the curves for creative efficiency and the number of group changes cross when $D_S = 10$, corresponding to the case where ten percent of the agents in the simulation can dissent. While increasing the number of dissenting agents above this value produces a greater number of group changes, such volume is achieved at a cost of decreasing creative efficiency. Although this calls for further work to clarify this finding, there are arguments that too many creative individuals decrease the effectiveness of innovation teams. For example, Jane Prichard and Neville Stanton[53] empirically investigated one of the propositions of Meredith Belbin's Team-Role Theory by comparing whether a team of "Shapers" – a Belbin team role associated with being creative – performed differently than a mixed team in a management strategy game. Prichard and Stanton's study found that a team of exclusively creative people performed less effectively than a more balanced team. Similarly, the argument that teams composed entirely of creatives are not always productive[54] is relevant to interpret these simulation outcomes.

53 Jane S. Prichard and Neville A. Stanton, "Testing Belbin's Team Role Theory of Effective Groups," *Journal of Management Development* 18, no. 8 (1999): 652–65, DOI: https://doi.org/10.1108/02621719910371164.

54 Csikszentmihalyi and Epstein, "A Creative Dialogue."

The analysis of average outcomes enables reasoning about creativity in organizations to an extent. However, following practices from the experimental study of creative ideation,[55] extreme value theory provides a complementary perspective on the behavior of these models. Recall that this is feasible here because these models are stochastic, which constitutes a reasonable way to deal with non-deterministic systems where multiple unforeseen conditions interact to shape outcomes. Therefore, we now look at the *success rate* of group creativity – the *realization* of the group's creative capacity. Cases where this occurs we label here as "innovation cases," which we define as those simulation cases with a large number of group changes ($\Delta g \geq 10$).

Figure 6 plots the number of innovation cases across D_S and D_D values. Firstly, regardless of the degree of dissent, with very small creative minorities – ten percent or less of agents able to create dissent – the number of innovation cases is negligible. In itself, this contradicts the earlier proposition that ten percent was somehow an optimal state, instead suggesting that at least ten percent of an innovation team needs to be creative in order to yield creative and efficient outcomes. However, the term "innovation case" should not be confused with real-world innovation. An innovation case in this study simply refers to a simulation where a larger number of group changes is registered – it does not take into account what the social and behavioral impact of continuously introducing ideas might have on a real team. Again, further work is needed to fully understand these outcomes. However, it is interesting that these simple models help to understand why creativity always comes at a price. In this regard, the earlier proposition that ten percent is an optimal state can be modified to suggest that ten percent is a threshold. Even though increasing the number of dissenting agents more than this will result in a loss of creative efficiency, this may be the price to pay if an organization wishes to grow creatively. Some innovation teams will be prepared to incur a greater cost than others to reap the rewards of creativity. In this sense, there may be a range of ten to thirty percent of dissenting agents that could be considered as a suitable composition for highly functional creative teams.

With high levels in the degree of dissent ($D_D = 6$), innovation cases rapidly increase to twenty percent of cases when one third of the group gains access to dissent. The number of innovation cases continues to increase steadily to approximately half of all cases once more than two thirds of members are change agents. When there is a moderate degree of dissent ($D_D = 3$), even when the entire group is made up of dissenting agents, innovation cases reach a maximum of twenty percent of cases. With low dissent ($D_D = 1$), innovation cases are extremely infrequent regardless of the ratio of change agents in a group, occurring only one percent of the time. This suggests that perhaps the creation of radical ideas is more significant in the propagation of a group change rather than in the number of creative agents.

55 Girotra et al., "Idea Generation and the Quality of the Best Idea," 3.

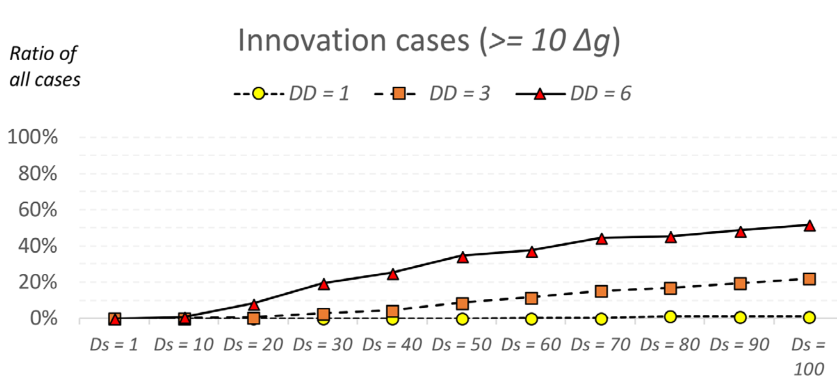


Figure 6 Number of innovation cases across D_S and D_D values. Copyright © 2018 Ricardo Sosa and Andy Connor.

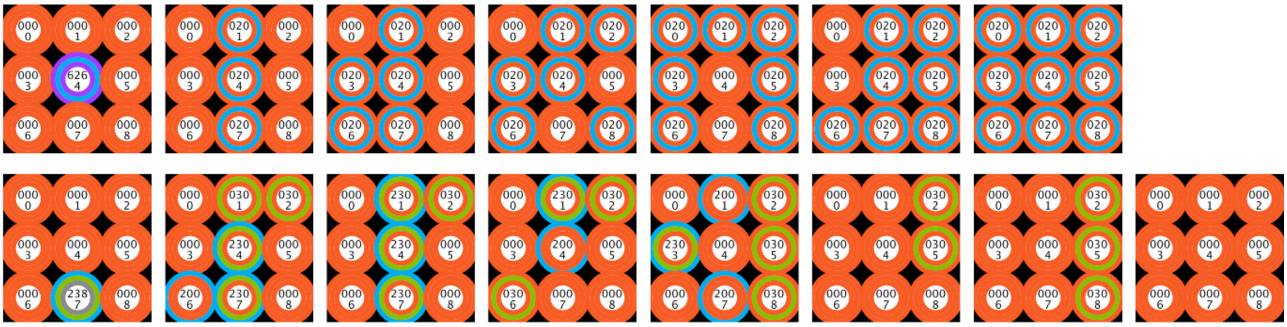


Figure 7 Types of change episodes during a simulation. The top row shows the entire group adopting the new value (group change); the bottom row shows the group returning to adopt the incumbent idea. Copyright © 2018 Ricardo Sosa and Andy Connor.

In addition to the quantitative analysis, agent-based simulations also support qualitative reasoning, in particular with regards to specific phenomena that help explain the dynamics of these systems. Figure 7 shows two types of change episodes during a simulation, represented in a 3 × 3 grid for clarity. Each episode is shown as a row: the first frame (left side) of both episodes shows the step when a change agent introduces a new idea to the group in response to a converged state on the dominant idea [0,0,0]. In the first episode (top row), the new idea [6,2,6] is generated by agent #4, and the second trait [2] is transmitted to neighboring agents #1 and #7, then ultimately triggers a group change in seven simulation steps when the entire group embraces the new value [0,2,0]. In the second episode (bottom row), agent #7 generates the new idea [2,3,8], and the first [2] and second [3] traits are initially disseminated as three variations: [2,0,0], [2,3,0] and [0,3,0]. These new ideas die out, and the group returns to unanimously adopt the incumbent idea [0,0,0].

What is noteworthy here is the possibility of considering the different types of group changes that can occur in these models, particularly with populations of hundreds of agents. A range with two extremes can be conceptualized in two ways. In groups with a minority of change agents (low D_S values) that make incremental changes (low D_D values), the dissemination of new ideas allows for higher control in group change. In groups where multiple new initiatives are made in short periods (high D_S values) and changes are more radical (high D_D values), the dissemination of new ideas supports higher rates of idea build-up, since new ideas and segments of new ideas are likely to interact and generate new variations by cross-over or recombination. This suggests that more nuanced strategies are needed by considering not only the average outcomes, or even the exceptional cases, but the type of innovation desired for a specific context. An increased and general creative participation in the organization could be more suitable when open-ended contributions and multiple viewpoints are required. In contrast, specialized and focused participation could be more suitable when a problem can lead to feature creep or group thinking.

Discussion

The previous section outlined the results of a number of simulation cases where the dissent in the simulation is varied. The immediate outcomes of these results have been described, but this section discusses the implications of those results in relation to the breadth-depth dilemma and the original premise that it is valuable to increase "the creativeness of five-hundred individuals each by, say, 1%."[56] The results of this modeling work suggest that the presumed benefits of wider creative participation as prescribed by Randall[57] are partial and could backfire when implemented in unsophisticated ways. While marginally increasing the change agency of all agents in a simulation does produce a higher number of group changes, the effects are larger when more effort is directed at channeling change agency in a

56 Randall, "Stimulate Your Executives to Think Creatively," 121.

57 Ibid., 121–28.

smaller proportion of agents. Indeed, the apparent best strategy – as suggested by these models – would be to greatly increase creativity across all agents. However, this would come at a loss of creative efficiency, essentially a proxy measure to represent the overhead of large number of creative individuals who have conflicting goals and ideas.

Clearly, there is scope here to determine the trade-off between a highly creative team and the creative efficiency of such a team, for which the best strategy will likely depend on the type of desired outcome and a range of contextual conditions. Hybrid strategies could be more appropriate in some contexts – for example, actively assigning dissenting roles in large groups or focusing explicitly on maximizing the degree of dissent in a small group. It may be that such hybrid strategies do not need to go very far to obtain the best results – anything beyond thirty to forty percent of dissent in a group seems to only increase the creative capacity of the group marginally.

In regards to firms' innovative capacity to deal with new change initiatives, the conditions in this particular model yield an average of ten successful group changes over 10^4 simulation steps. A very small number of exceptional cases reach twice that number, justifying the adequacy of applying extreme value theory in studies of innovation.

There are a number of limitations to the current work, which can be divided into two categories: internal limitations of the simulation model and external limitations that impact the perceived validity of the work. In terms of internal limitations, the main issue is the analogical nature of the simulation model. This was a purposeful decision: we decided to attempt to generate insight into the breadth-depth dilemma in the most elementary way, by testing whether agent based simulation has any potential to provide meaningful outcomes to help reason about this phenomenon. Having shown that agent-based simulation does have the potential to generate meaningful outcomes, a number of model extensions could help overcome some of the internal limitations of this work, such as adding evaluation functions, or manipulating the number of design features and traits in meaningful ways. For example, design features can be represented by utterances in language games.[58] Evaluation goals would allow researchers to include outputs in the analysis, for example when the agent group is able to find as many permutations or combinations that fit a preferred value range. Introducing variable, individual probabilities could also be examined. Grid properties could help model-specific conditions such as agent mobility and barriers that impede perfect communication. Further possibilities include the introduction of more realistic individual agent behaviors or the use of non-homogeneous agent types.

In general, the challenge with such extensions is to define and manipulate model variables that do represent specific target conditions, and to test if and how adding layers of complexity adds meaning and clarity and enables traceability of system interactions. Even if such options provide a more complex model, there remains an open question as to whether or not the outcomes derived through the use of agent based simulation bears any resemblance to the performance and behavior of real world innovation teams. Although this can be achieved by comparison to existing studies of empirical team performance, there is the possibility that discrepancies between the studies may still impact the validity of the outcomes. One of the key directions for future work is therefore the conduct of a real-world evaluation of team creativity that is later modeled using some of the more complex agent simulations as outlined above as necessary. The systematic examination of parameter ranges could help reveal and anticipate the effects of different policies and strategies that could be subsequently tested in laboratory experiments.

58 Rob Saunders, "Towards Autonomous Creative Systems: A Computational Approach," *Cognitive Computation* 4, no. 3 (2012): 221.

Conclusions

The work we present here examines the apparent dilemma of breadth-first vs. depth-first strategies in creative organizations. The study proposes to reconsider first principles and to examine key components of organizational creativity using computational simulations to systematically reason about change agency in innovation teams. This work suggests a number of interesting possibilities to extend the scope of organizational creativity research. First, the model shows that adding more individuals that give new ideas to a group does not necessarily increase the potential for change. Depending on mediating factors, groups with fewer change agents can outperform groups with more change agents, or at least the gains cannot be expected to be linear. Diminishing returns in creative participation would suggest that focusing on some – but not necessarily all – individuals to generate more radically new ideas may be more critical than simply opening creative ideation to larger groups.

To overcome challenges such as idea blocking during brainstorming sessions, hybrid conditions have been examined that combine the benefits of individual and group ideation.[59] The work presented here suggests other ideation strategies where some members of an innovation team (arguably around one-third) specialize in generating new radical ideas, and the rest focus on taking those ideas on board and making improvements, combinations, and extensions. Field studies have shown a similar role specialization in professional design teams, with idea-givers and idea-takers combining their strengths.[60] One possible advantage of such balance of exploration and exploitation of new ideas would be to enable the intentional formation of chains or trains of ideas to examine the possible entailments and alternatives of radically new ideas.

The concept of introducing a small number of radically new ideas to promote creative performance tends to go against conventional ideation wisdom, which promotes the development of as many ideas as possible.[61] In many respects, the intention of ideation is a process of creating enough ideas that the organization is lucky enough to find an innovative one. Interestingly, laboratory studies have shown that having too many ideas makes it harder for these ideas to be screened and evaluated effectively. In particular, Bruce Reining and Robert Briggs[62] identified "a curve with a positive but decreasing slope in ideation functions [showing that] idea-quantity may not be a useful surrogate for idea-quality in certain circumstances."[63] Although the study of ideation sessions in terms of idea quantity and quality is not directly related to the outcomes of this study, some have noted that "exposure to ideas from others is both distracting and stimulating,"[64] and it has also been seen that an increase of group size in ideation sessions can decrease the number of ideas generated.[65] The recurring theme in the literature in terms of the payback for creativity efforts is consistent with the modeling presented here. The trade-off identified in this current study confirms that the greatest number of group changes is achieved at a significant loss of creative efficiency. This concept of diminishing returns is useful to frame questions and advance early implications for practice.

Initial outcomes of this work, when combined with knowledge from existing empirical studies of real world innovation teams, would suggest that there is no clear strategy for resolving the breadth-depth dilemma. However, there seems to be value in monitoring and supporting a creative critical mass – rather than prescribing an elitist creative class – in an organization, and that such a creative critical mass may best be achieved by combining a small number of highly creative individuals distributed throughout the team in conjunction with strategies to increase the creative engagement of every team member. We will explore this in future work using computational simulation as a method for different team composition strategies.

59 Girotra et al., "Idea Generation and the Quality of the Best Idea," 13.

60 Kimberly D. Elsbach and Francis J. Flynn, "Creative Collaboration and the Self-Concept: A Study of Toy Designers," *Journal of Management Studies* 50, no. 4 (2013): 524, DOI: https://doi.org/10.1111/joms.12024.

61 Osborn, *Applied Imagination*.

62 Bruce A. Reinig and Robert O. Briggs, "On the Relationship between Idea-Quantity and Idea-Quality during Ideation," *Group Decision and Negotiation* 17, no. 5 (2008): 403–20, https://doi.org/10.1007/s10726-008-9105-2.

63 Ibid., 419.

64 Paul B. Paulus, Nicholas W. Kohn, Lauren E. Arditti, and Runa M. Korde, "Understanding the Group Size Effect in Electronic Brainstorming," *Small Group Research* 44, no. 3 (2013): 335, DOI: https://doi.org/10.1177/1046496413479674.

65 Thomas J. Bouchard Jr. and Melana Hare, "Size, Performance, and Potential in Brainstorming Groups," *Journal of Applied Psychology* 54, no. 1 (1970): 53, DOI: https://doi.org/10.1037/h0028621.