Evolutionary perspectives on collective decision making: Studying the implications of diversity and social network structure with agent-based simulations

Hiroki Sayama  
Collective Dynamics of Complex Systems Research Group  
Departments of Bioengineering & Systems Science and Industrial Engineering  
Binghamton University, State University of New York, Binghamton, New York  
Phone: (607) 777-4439  
Fax: (607) 777-5780  
Email: sayama@binghamton.edu

Shelley D. Dionne  
Center for Leadership Studies, School of Management  
Binghamton University, State University of New York, Binghamton, New York

Francis J. Yammarino  
Center for Leadership Studies, School of Management  
Binghamton University, State University of New York, Binghamton, New York

Abstract

Collective, especially group-based, managerial decision making is crucial in organizations. Using an evolutionary theory approach to collective decision making, agent-based simulations were conducted to investigate how collective decision making would be affected by the agents’ diversity in problem understanding and/or behavior in discussion, as well as by their social network structure. Simulation results indicated that groups with consistent problem understanding tended to produce higher utility values of ideas and displayed better decision convergence, but only if there was no group-level bias in collective problem understanding. Simulation results also indicated the importance of balance between selection-oriented (i.e., exploitative) and variation-oriented (i.e., explorative) behaviors in discussion to achieve quality final decisions. Expanding the group size and introducing non-trivial social network structure generally improved the quality of ideas at the cost of decision convergence. Simulations with different social network topologies revealed that collective decision making on small-world networks with high local clustering tended to achieve highest decision quality more often than on random or scale-free networks. Implications of this evolutionary theory and simulation approach for future managerial research on collective, group, and multi-level decision making are discussed.

Keywords: collective decision making, evolutionary theory, agent-based simulation, group homogeneity and heterogeneity, social networks
Evolutionary perspectives on collective decision making: Studying the implications of diversity and social network structure with agent-based simulations

Abstract

Collective, especially group-based, managerial decision making is crucial in organizations. Using an evolutionary theory approach to collective decision making, agent-based simulations were conducted to investigate how collective decision making would be affected by the agents’ diversity in problem understanding and/or behavior in discussion, as well as by their social network structure. Simulation results indicated that groups with consistent problem understanding tended to produce higher utility values of ideas and displayed better decision convergence, but only if there was no group-level bias in collective problem understanding. Simulation results also indicated the importance of balance between selection-oriented (i.e., exploitative) and variation-oriented (i.e., explorative) behaviors in discussion to achieve quality final decisions. Expanding the group size and introducing non-trivial social network structure generally improved the quality of ideas at the cost of decision convergence. Simulations with different social network topologies revealed that collective decision making on small-world networks with high local clustering tended to achieve highest decision quality more often than on random or scale-free networks. Implications of this evolutionary theory and simulation approach for future managerial research on collective, group, and multi-level decision making are discussed.

Keywords: collective decision making, evolutionary theory, agent-based simulation, group homogeneity and heterogeneity, social networks
Evolutionary perspectives on collective decision making:
Studying the implications of diversity and social network structure with agent-based simulations

1 Introduction

Collective decision making plays an increasingly important role in society and organizations today (Mannes 2009; Kerr and Tindale 2004). In high-tech industries, for example, the number of engineers participating in the design of a single product can amount to hundreds or even thousands due to the increase of the product’s complexity far beyond each individual engineer’s capacity, which almost inevitably results in suboptimal outcomes (Klein et al. 2003a). Another example is the online collective decision making among massive anonymous participants via large-scale computer mediated communication networks, including collective website/product rating and common knowledge base formation (O’Reilly 2005). In these and related cases, participants and their societal or organizational structure may influence the final outcome of decision making processes. The complexity of the process is more pronounced when the participants are heterogeneous and are embedded in a topologically non-uniform network with differential distribution of power, as in most organizations and social systems. The dynamics of collective decision making in such conditions are poorly understood, and as such poses a significant challenge for the social and organizational sciences.

Evidence of this challenge exists within the leadership, psychology and organizational behavior/management disciplines where collective dynamics, using both experimental and applied studies, generally emphasize linear statistical relationships between specific, narrowly defined team- or individual-level variables (Kerr and Tindale 2004; Salas et al. 2004; Dionne et al. 2012). Traditional studies seldom account for nonlinear dynamical processes that take place in a high-dimensional problem space and/or non-trivial social structure where interactions occur within a networked organizational structure. Abbott (2001) highlights this problem within the social sciences by discussing a “general linear reality,” where mainstream social science theories and methods treat linear models as actual representations of social systems. Further, Meyer et al. (2005) assert that reinforcing assumptions of linearity and equilibrium have “blocked the investigation of a family of interesting problems of great practical import (p. 456).” In other words, researchers point to an oversimplification of collective processes in general and collective decision making in particular.

Examples of recent research not necessarily following a “general linear reality” to model inherent complexity in social systems are found within the complex systems research community, where social processes are studied using a mathematical/computational modeling approach (Simon 1955; Axelrod 1981; Epstein and Axtell 1996; Bar-Yam 1997; Bar-Yam 2004; Gilbert and Troitzsch 1999; Sterman 2000; Epstein 2006; Miller and Page 2007; Sayama, Farrell and Dionne 2011; Yamanoi and Sayama
Because emphasis is on emergent dynamical behavior of systems caused by nonlinear interactions among massive numbers of parts (a pervasive phenomenon also found in fields such as physics, biology, sociology, psychology, economics, engineering and computer science), advances in other scientific domains for modeling complex systems may benefit organizational research (Carroll and Burton 2000).

Thus, the aim of this research is to enhance performance of groups and other entities involved in collective decision making. Collective decision making implies a larger clustering of individuals with interdependency based on shared expectations or hierarchy. Collectives can be complicated structures and include individuals, groups, functional business units and even larger industry alliances and networks (Dansereau, Alutto and Yammarino, 1984; Yammarino and Dansereau 2002; Yammarino et al. 2005). We seek to improve our understanding of both the dynamic nature of the collective decision process, as well as the influence of diversity and social connectivity issues related to decision making involving a number of participating group members. Employing evolutionary views in understanding decision making enables a uniform, straightforward explanation of many empirical findings about the effects of group composition and dynamics on group performance. Considering specific within-group level issues regarding the collaborative process of decision making also may offer clarity regarding the influence of group composition on performance. Borrowing from advances in complex systems enables a dynamic, within-level examination of an evolutionary collective decision process via computational modeling.

To better understand decision making in collective and dynamic environments, we offer an alternative model of collective decision making based on evolutionary theory, examining the issues of diversity/heterogeneity in decision making groups and the effects of non-trivial social network structure among the group members on decision outcomes. We first explore how evolutionary theory can address complex changes over time by providing an explanatory framework for collective decision processes, and then discuss how specifying a targeted level of analysis can inform appropriate interpretation and limitations of decision making in dynamic environments. Finally, a computational agent-based model (Epstein 2006) with an evolutionary focus on collective decision making in groups and social networks is developed and tested, with diversity of problem understanding and behavioral patterns and social network structure manipulated as experimental variables.

Specifically, four recommendations can be adapted to advance our theoretical understanding of collective decision making in complex social systems: 1) consider the impact of time; 2) study situations in flux; 3) incorporate nonlinear concepts into evolutionary theorizing; and 4) design multi-level research (Meyer et al. 2005) that takes into account complex social network topologies. These guidelines provide a starting point for investigating the complexity of collective decision making with an evolutionary and multi-level, network-oriented framework. Prior dynamical modeling in organizational research may have
considered the impact of time and situations in flux; few if any, however, have included specific evolutionary and multi-level, network-oriented concepts.

2 Evolutionary theory and collective decision making

Evolutionary theory describes adaptive changes of populations primarily by combining mechanisms of variation and selection (Futuyma 2005; Wilson 2005). The roles of these two mechanisms are similar to what was already discussed as “exploration” and “exploitation” in organizational learning literature (March 1991). In biological evolution, variation is caused primarily by internal genetic mechanisms (e.g., mutation and recombination) and plays an exploratory role that could potentially lead to a novel possibility of life form, but it usually reduces immediate competitiveness of a population. In contrast, selection is caused primarily by external environment (e.g., natural and sexual selection) and plays an exploitative role that enhances the presence of successful entities (genes, individuals, or groups) and eliminates unsuccessful ones, reducing the number of possibilities while potentially improving the overall competitiveness of the population. A dynamically maintained balance of the two mechanisms is the key to a successful evolutionary adaptation (Mitchell et al. 1991).

We propose that decision making processes within a collective (such as a group or an organization) also may be viewed through a similar lens, by shifting the viewpoint from members’ personal properties (a more traditional psychological and decision making approach) to dynamical changes of ideas being discussed within the collective, where populations of potential ideas evolve via repetitive operations such as reproduction, recombination, mutation, and selection of ideas, conducted by participating members (Sayama and Dionne 2013a; Sayama and Dionne 2013b). Table 1 provides a brief summary of the evolutionary framework we propose by illustrating how some key evolutionary operators and concepts can be linked to decision factors. We take this approach because evolutionary theory provides a powerful theoretical framework that can readily address complex changes of systems over time in extremely high-dimensional problem space, and also its explanatory mechanisms (heredity, variation, and selection) are theoretically clean-cut and easily accessible (Wilson 2005). Moreover, by shifting the viewpoint from individuals to ideas, a model could be liberated from the commonly used but somewhat artificial assumption that each individual always has his/her decision in mind. Rather, various ideas developed within and among participants are collectively reflected in the idea population, to which diverse within-individual cognitive/behavioral patterns can be easily applied as a set of multiple evolutionary operators simultaneously acting on the same, shared idea population.

| Insert Table 1 Here |
|---------------------|

2.1 Evolutionary operators and collective decision processes
Many evolutionary operators (Mitchell 1996; Fogel 1995) can be conceived as a representation of diverse human behaviors in discussion and decision making processes (Sayama and Dionne 2013a; Sayama and Dionne 2013b; also see Table 1). For a selection-oriented example, replication of an idea is a form of positive selection, where the popularity of an idea is increased within the population of ideas. This action can be considered as advocacy of a particular idea under discussion. Similarly, criticism against an idea may also be considered a form of negative, subtractive selection. Criticism singles out an idea with poor utility and reduces its popularity within the population of ideas. Both positive and negative selections seek to narrow decision possibilities based on utilities (“fitness”) of ideas perceived by participants. For a variation-oriented example, random point mutation makes random changes to existing ideas by asking “what if”-type questions. Likewise, intelligent, or hill-climbing point mutation (Klein et al. 2003b), which is not present in biological evolution but may be relevant to include in collective decision making, initially begins like random point mutation, however several variations from the original idea may occur, with final selection of the idea with the highest perceived utility. Recombination represents the creation of a new idea by crossing multiple existing ideas. These variation-oriented evolutionary operators enhance the explorative capabilities of the population, but generally reduce their immediate fitness.

To illustrate the typical evolutionary operators that may be present in collective decision making, consider a collective decision task for a design and marketing group from a toy maker that wants a stronger presence in the girls toys market. The company currently has a strong presence in the boys toys market with a construction block toy, but the toy’s predominantly primary and/or dark color blocks, rectangular and square shapes that construct buildings and vehicles, and generic figures that look like little men have not had significant appeal to girls. The team is charged with moving into the girls toys market to appeal to the other 50% of toy users. Here are some examples of evolutionary operators in action.

2.1.1 Replication

One designer offers an idea to increase the color palate currently offered in the bricks, adding pastels and lighter colors. Another designer offers an idea to produce new shapes of blocks besides predominantly four-sided, regular blocks. Another designer thinks they should consider developing snap together jewelry. A marketing member of the team states they do not have an idea, but they really like the new color palate idea. This concurrence with a prior idea increases its popularity by adding an exact copy of an idea that already exists in the population, and is a form of advocacy.

2.1.2 Random Point Mutation

One designer takes the new color palate idea and wonders “what if” figures could be color coordinated as well, and moreover, some figures could look like little women, not just little men. The
copied idea (new color palate) is offered, but with a focus on including new figure designs (i.e., different gender) that could be outfitted in different colors. This random change to an existing idea represents random point mutation.

2.1.3 Intelligent Point Mutation

Consider the idea generated above, where new figures of both men and women have color palates such as dark and bright colors on men figures and light and pastel colors on women figures. After a period of reflection of some of team’s ideas under consideration, a new idea emerges. For example, after the color palette idea emerges, each of the designers considers this new direction for a while. Then, someone suggests, with confidence, that adding accessories such as hats, shoes, hair and clothing, to customize the figures, would be the best way to go. His/her confidence comes from several internal trial-and-error thought processes inside him/her, which makes his/her suggestion more intelligent than other random “what-if” suggestions.

2.1.4 Recombination

Consider a creativity exercise for the toy makers where all generated ideas are written down and placed into a jar. Two ideas are pulled from the jar randomly and the team is told to generate new ideas by linking them together. For example, a person may draw the ideas “new shapes for blocks” and “accessories for male and female figures” to develop an idea that accessories should snap on using the same technology that snap building blocks together. This idea means some new shapes (i.e., round blocks for hats, hair) need to be constructed and applied to the figures. This combines accessorizing figures with new shapes for building blocks (i.e., recombination of ideas).

2.1.5 Subtractive Selection

In the discussion, someone may state that snap together jewelry moves too far away from the brand and therefore should be stricken from the idea list. This represents subtractive selection. This reduces the popularity of the idea in discussion so that its chance of being considered favorably may become lower.

Moreover, besides the evolutionary operators, other evolutionary concepts can be adapted or applied to a collective decision making process as well. A group’s problem or decision space may be likened to a genetic possibility space. A potential idea, or set of choices for all aspects of a problem, may be akin to a genome. Similarly, a particular aspect of the problem could map to a locus on a genome, whereas a specific choice made for a particular aspect may be likened to allele (i.e., specific gene) on a locus. Adding to parallels in evolutionary framework application to decision making, consider that a set of potential ideas under discussion may map to the concept of population. Additionally, perceived (or real) utility value of a potential idea may represent fitness, and the increased utility value achieved by the idea population may be likened to adaptation.
As summarized in Table 1, using an evolutionary theory perspective, we define collective decision making as *ecologies of ideas over a social network habitat, where populations of potential ideas evolve via continual applications of evolutionary operators such as replication, recombination, mutation, selection, and migration, each conducted by participating group members*.

Thus, there appears to be an intuitive parallel between an evolutionary framework and a collective decision process. Applying an evolutionary theory to collective decision making seems consistent with the spirit of the Meyer et al. (2005) suggestions regarding improvement of research techniques to better reflect situations in flux and nonlinear concepts within an evolutionary framework. The next section addresses another important Meyer et al. (2005) concern: multi-level research.

### 3 Levels of analysis and evolution

Evolutionary biologists Wilson and Wilson (2008) reiterate the link between adaptation and a specific regard for levels of analysis in reviewing the history of multi-level selection theory. Wilson and Wilson’s (2008) recent evolutionary perspective on multi-level selection challenges researchers to evaluate the balance between levels of selection, specifically where within-group selection is opposed by between-group selection. This deeper view of a multi-level evolutionary process can be applied to organizational research as well (Yammarino and Dansereau, 2011). Research on both levels of analysis within organizational behavior (Yammarino and Dansereau 2002; Dansereau et al. 1999; Klein et al. 1994; Dansereau et al. 1984) and on group collaborative processes (Chang and Harrington 2005, 2007; van Ginkel and van Knippenberg 2008) highlight the importance and value of explicitly viewing the heterogeneity and/or homogeneity of the group and/or collective. This homogeneity and heterogeneity perspective can be viewed as a within-level examination, where the entity of interest remains the group, but there can be at least two valid views at the collective level: homogeneity (what evolutionary theory refers to as a between-group focus) and heterogeneity (what evolutionary theory refers to as a within-group focus).

These two different perspectives for viewing groups are aligned with the concept of group wholes and group parts, a theoretical distinction developed within organizational behavior and applied to various research domains such as leadership and group dynamics (Yammarino and Dansereau 2002, 2011; Yammarino et al. 2005; Dansereau et al. 1999; Klein et al. 1994; Dansereau et al. 1984). A group wholes perspective indicates homogeneity within the group, and the relevant focus on the entity (i.e., groups) would be between groups, since differences within groups would be considered random (i.e., error). Conversely, a group parts perspective indicates heterogeneity within groups, and the relevant focus on the entity (i.e., groups) would be within groups, since differences between groups would be considered random (i.e., error).
3.1.1 Homogeneity (group wholes, or between-group differences condition)

The concept of differing perspectives on an entity can provide more specific insights regarding group processes, in that phenomena of interest may be more relevant when groups are homogeneous regarding their membership, but differ in characteristics from other groups. In this wholes condition, all members within a group possess the same (or at least very similar) characteristic, while in the next group all members possess some other characteristics that first group perhaps did not. Another view can be taken concerning amounts of a characteristic present, where members of a group would possess the same amount of a characteristic, while members of the next group also would possess the same characteristic, but all members would have more of that characteristic, or all members would have less of that characteristic. This view represents one patterning of characteristics and individuals in groups—homogeneity.

3.1.2 Heterogeneity (group parts, or within-group differences condition)

From a contrasting perspective, phenomena of interest may be more relevant when groups are heterogeneous regarding their memberships. In this case, members within a group would have varying degrees of a characteristic, and the next group also would have members with varying degrees of a characteristic, and the same applies for all groups. This view is another patterning of characteristics and individuals in groups—heterogeneity.

3.2 Decision research and levels of analysis

Precedent for a broadly applicable modeling approach has been established in the evolving architecture of problem-solving networks (Chang and Harrington 2007). This research enabled consideration of a generic problem-solving environment and assessment of emergence regularity of connectors within the problem environment. Moreover, Chang and Harrington’s research related to the modeling of both homogenous agents (2005) and heterogeneous agents (2007) is of interest to our work. Specifically, we use homogeneity and heterogeneity of groups as means for examining levels of analysis issues related to collective and/or group processes.

Although Chang and Harrington’s (2005, 2007) modeling examines a more multi-level relationship between agents (individuals) and the larger environment, we are concerned with examining a within-group, collective or collaborative decision process, where individuals would not be considered outside of the group. Our examination of a unique within-level evolutionary process, employing both within-group and between-group perspectives, is a novel view of collaborative decision making and advances the understanding of a collective environment. And, while Meyer and colleagues (2005) called for more multi-level research, this unique and deliberate view within a single level of analysis, but employing multiple perspectives (i.e., wholes/homogeneity and parts/heterogeneity) on that level, also advances social research in that it moves the field away from an oversimplified view of groups.
A critical distinction of our research is that we are interested in examining a type of process occurring within the group over time, not necessarily the specific variables within the process. Dansereau, Yammarino and Kholes (1999) highlighted the nature of such research on differing perspectives of an entity and entity changes rather than on changes in specific variables over time. Because we are interested in the type of process occurring within the group during decision making, we agree with Dansereau and colleagues (1999) that the variables that characterize the level may change or remain stable, but the level of interest remains the same (in our case, the level of interest remains the group).

Related, diversity and/or homogeneity and heterogeneity of groups and information sharing (Gruenfield et al. 1996; Gigone and Hastie 1993; Stasser and Stewart 1992; Stasser and Titus 1985) present an additional layer to the decision process that requires consideration. Nijstad and Kaps (2007) noted that homogeneity of preferences leads to a lack of sharing of unique information within a group, whereas preference diversity prevented premature consensus of the group and facilitated unbiased discussions of preferences. Lightle, Kagel and Arkes (2009) indicated individual heterogeneity in information recall may play an role in failure to identify hidden profiles within groups. Similarly, van Ginkel and van Knippenberg (2008) found that groups in decision tasks performed better when task representations emphasized information elaboration and the group acknowledged they shared the view of the task representation. These findings reinforced that groups tend to focus on finding common ground and reaching consensus, but highlighted the importance of understanding, as a group, the task representation. This shared understanding could be critical to group success and adaptation, and as such, we include an indicator of how well group members share a view of what constitutes the problem.

Although advancements in decision research continue, many continue to focus on individual-level aspects related to a decision maker, such as how they adopt practical behavior rules (Maldonato 2007) or identification of performance moderator functions that may affect individual behaviors in simulated environments (Silverman et al. 2006). While multi-level implications exist in recent decision research (Nijstad and Kaps 2007; Van Ginkel and van Knippenberg 2008), there is limited specific focus on within-group level aspects of a decision process. Moreover, Maldonato (2007) notes there is likely no best way to view the decision process. As such, there may be some benefit to development of a preliminary model exploring the effect of membership similarity and differences on group-based decision processes from evolutionary and levels of analysis-based perspectives. Development of such a model advances understanding of collective decision making in that it builds on prior key decision research (Nijstad and Kaps 2007; Chang and Harrington 2007; Kock 1999, 2004; Knudsen and Levinthal 2007), incorporates the suggestions of improving organizational research offered by Meyer et al. (2005), and incrementally increases the complexity yet fuller understanding of the phenomena represented in prior collective decision models. The specific model assumptions are discussed in the next section.
4 Modeling Dynamic Collective Decision Making

Applying computational modeling to dynamical processes such as collective decision making may enable organizational researchers to more appropriately represent the potential nonlinearity of a collective process. For example, interdisciplinary exchange may have informed recent organizational research which includes several dynamical models proposed for collective decision making over social networks that consist of many interacting individuals (Klein et al. 2003a; Battiston et al. 2003a; Battiston et al. 2003b; Rodriguez and Steinbock 2004). These models, primarily an extension of models developed in theoretical physics, provide a novel, promising direction for research on group dynamics and collective decision making. A limitation of this research and more specifically its ability to model complex social systems, however, is the consideration of only simple problem spaces, typically made of binary or continuous numerical choices between 0 and 1.

Increasingly complex nonlinear problem space has been modeled (Klein et al. 2003b; Rusmevichientong and Van Roy 2003, Klein et al. 2006) to consider interdependent networks of multiple aspects of a complex problem. This research, however, was not modeled in a collective, nontrivial societal context. This is not surprising because problems arise with collective decision models in that they commonly assume every individual agent has or makes his/her own decision. Following these assumptions, the collective decision making dynamic is represented as a process of propagation, interaction and modification of individual decisions. This is an over-simplified assumption compared to actual cognition processes and behavior of individuals and collectives (Lipshitz et al. 2001; Salas and Klein 2001). Individuals often keep multiple ideas in mind and may remain undecided during or even after a collective-level decision emerges. The collective decision forms not just through the interactions of individual decisions but also through the more active, dynamic exchanges of incomplete ideas and mental models being developed by every individual (Dionne, Sayama, Hao and Bush 2010). Such within-individual mental and behavioral complexity has just begun to be included in computational models (c.f., Knudsen and Levinthal 2007; Dionne and Dionne 2008), and should be taken into account to a greater extent in order to investigate more detailed, dynamic aspects of collective decision making (Salas and Klein 2001).

Although powerful in their ability to examine beyond the “general linear reality,” dynamical models of collective decision making are still at an initial, preliminary stage. However, if limitations in current collective decision research (such as those over-simplifications noted above) are straightforwardly addressed in a single model, the resulting model may be too complex to be useful and effective for scientific enquiries. Because so many details would be involved, the model may not be “transparent” enough to offer clear relationships between assumptions and outcomes (Miller and Page 2007, Adner et al. 2009, Ren, Carley and Argote 2006). Therefore, collective decision making models need to carefully
balance the ability to represent the complexities of dynamical social interactions against the ability to straightforwardly explain collective decision processes and outcomes.

In view of such contexts for computational models of social and organizational sciences, an agent-based model has already been proposed that applied the evolutionary framework introduced in the prior section to model collective decision making processes within a small-sized, well-connected social network structure (Sayama and Dionne 2013a, Sayama and Dionne 2013b). This model was used to conduct a specific within-level analysis on how homogeneity or heterogeneity of goals and decision utility functions among participants affect dynamics and the final outcomes of their collective decision making.

We present here a new agent-based model that implements a systematic control of agents’ behavioral balance between selection-oriented and variation-oriented operators, together with much larger, non-trivial social network structure on which agents exchange ideas locally. We believe that our approach to social dynamics research can move the social sciences away from an oversimplified view in that it investigates nonlinear change in organizational research (Meyer et al. 2005). Moreover, examining a new theoretical framework is consistent with development of computational models, as Adner et al. (2009) recognize that simulation is generally an exercise in theory building.

4.1 Model assumptions

4.1.1 Groups, or social networks

Our model assumes that \( N \) agents are connected to a finite number of other agents via links through which ideas are exchanged. Each agent can memorize multiple ideas in its mind. Multiple copies of a single idea may be present, which represents a form of relative popularity for that idea to the agent. Each agent is initialized with a small number of randomly generated ideas in its mind at the beginning of a simulation. The agents begin to perform a set of actions on the population of ideas in their minds repeatedly for a fixed number of iterations. The order by which the agents take actions is randomized every time, but it is guaranteed that every agent does take exactly one action per iteration. This round-robin format is commonly used in idea sharing phases with decision making techniques such as a nominal group technique and various brainstorm initiatives (Paulus and Yang 2000; Van de Ven and Delbecq 1974). As such, the number of actions performed in a simulation is a product of the number of agents \( N \) and the number of iterations \( T \).

While other group decision research has modeled hierarchical teams in decision models (c.f., Dionne and Dionne 2008), we make no assumptions regarding predetermined leadership and/or abilities within the team as several teams in organizations are self-led and share leadership responsibilities (Salas, Stagl and Burke 2004; Salas and Klein 2001). We investigate the potential impact of varying membership within the group (i.e., no assumption of identical abilities or uniform connectivities in general) on the
potential pool of ideas. Since no single person is powerful enough to eliminate an idea from the group (i.e., shared leadership), we assumed that actions were performed on single copies of an idea, not the equivalence set of all idea replicates (described in detail below).

4.1.2 Utility functions

The use of utility functions in collective decision research is a natural outgrowth of earlier research by Hollenbeck et al. (1995) noting team decision making theory can be considered an adaptation of individual decision models and decision alternatives can vary along a univariate continuum. This view supplies a multi-level (e.g., group parts and group wholes) perspective and allows for adaptation of individual utility functions throughout a collective decision process. Both factors can be represented and/or captured by collective decision computer models (c.f., Dionne and Dionne 2008). As such, the use of utility functions contributes to the development of this model as well.

Agents develop and exchange ideas in an $M$-dimensional binary problem space, with a total of $2^M$ possible ideas. For a simulation, every idea has an inherent utility value specified by a true utility function $U_T$ that is unavailable to any agent. Individual agents perceive idea utility values based on their own utility functions $U_j$ constructed by adding noise to the master utility function $U_M$. The master utility function $U_M$ may or may not be the same as $U_T$, depending on the possibility of group-level bias (explained below). This initialization reflects the notion that today’s organizational problems are too complex for a single individual to solve (i.e., true utility value not available to any of group members), and therefore groups or collectives are assembled to solve problems and make decisions (Klein et al. 2003a; Salas and Klein 2001). Ideally, collectives function by bringing unique information from members (i.e., individual utility functions) together in such a way as to produce ideas that exceed an individual’s idea development capability (Kerr and Tindale 2004).

We develop a semi-continuous assignment of utility values in the problem space in the following way. First, $n$ representative ideas $S = \{v_i\} \ (i = 1\ldots n)$ are randomly generated as strings of bits (zeros and ones), where each $v_i$ represents one idea of $M$ bits. One idea is assigned the maximum utility value, 1, and another, the minimum utility value, 0. The remaining $n – 2$ ideas are assigned a random real value between 0 and 1. This action ensures that the entire range of utility values is always from 0 to 1, which makes it easier to compare different simulation results. The detailed shape of the distribution varies within this range for different simulation runs.

The utility values of all possible ideas in the domain of the true utility function are defined by interpolation using the utility values of representative ideas in $S$. We use the Hamming distance as a measure of dissimilarity between two bit strings, which reflects the number of bits for which two strings vary (Hamming 1950). With this measure, the utility value of each possible idea $v$ not present in $S$ is calculated as a weighted average of the utility values of the representative ideas as follows:
\[ U_T(v) = \frac{\sum_{i=1}^{n} U_T(v_i) \cdot D(v_i, v)^2}{\sum_{i=1}^{n} D(v_i, v)^2} \]  
\text{where } v \not\in S \text{ is the idea in question, } U_T(v_i) \text{ is the utility of a representative idea } v_i \text{ in } S, \text{ and } D(v_i, v) \text{ is the Hamming distance between } v_i \text{ and } v. \text{ This weighted average based definition gives the true utility function } U_T(v) \text{ a reasonably "smooth" utility value assignment in a high-dimensional problem space (i.e., similar ideas tend to have similar utility values in general). Such an underlying structure of the problem space is necessary for intelligent collective decision making to be better than unintelligent random trial and error.}

Note that the utility landscape construction method described above is different from that of Kauffman’s N-K fitness landscapes often used in management science (Kauffman 1993; Levinthal 1997; Rivkin 2000). We chose this approach because our method makes it easier and more straightforward to introduce group-level bias, i.e., discrepancy between the true and master utility functions.

Group-level bias is simulated by adding random perturbation when the master utility function \( U_M \) is constructed from the true utility function \( U_T \). Specifically, a bias \( \beta \) is included in the master utility function by flipping bits with probability 0.25\( \beta \) per bit on representative ideas in \( S \), and by adding a random number in \([-\beta, \beta]\) to utility values of the representative ideas. Their utility values are then renormalized to the range [0, 1]. The master utility function \( U_M \) is then generated from these perturbed representative idea set in the same way as in Eq. (1). Adding bias changes fidelity of information at the group level, where \( \beta = 0 \) denotes perfect understanding of the problem (\( U_M = U_T \)) as a collective, while complete lack of understanding is asymptotically approached as bias increases.

Moreover, each agent will unconsciously have a different set of utility values for the possible ideas of the problem. Individual utility functions \( U_j(v) \) \((j = 1 \ldots N)\) are generated by adding random noise to the master utility function \( U_M \) so that:

\[ U_j(v) \in [\max(U_M(v) - \xi, 0), \min(U_M(v) + \xi, 1)] \]  
\text{for all } v, \text{ where } \xi \text{ is the parameter that determines the range of noise. Figure 1 shows an example of such individual utility functions in contrast to the master utility function. As bounded rational actors, agents are not aware of the full set of alternatives available to them, nor can agents fully specify potential action-potential outcome causal linkages (Gavetti and Levinthal 2000). Therefore agents in our model are not aware of the entire structure of their own individual utility functions. They cannot tell what ideas would produce global maximum/minimum utility values, though they can retrieve a utility value from the function when a specific idea is given, which is a common assumption made in complex global optimization problems (Horst, Pardalos and Thoai 2000).}
Although not explicitly aware of their entire utility function structure, agents in a homogeneous condition can represent a “group wholes” view, where agents have similar utility functions within the group, but across groups there exist different utility functions; yet all members of each particular group share a strong degree of similarity with their groups’ unique utility function. Conversely, a heterogeneous condition can represent a “group parts” view, where agents have different utility functions within the group, and these utility functions are generally not similar. As such, within each group unique and/or diverse utility functions prevail, but across groups, this pattern is not unique, as group after group exhibits this same type of uniqueness among its members.

We recognize that a homogeneous group with no group-level bias would be unlikely in actual groups and collectives. Reduction of a group-level bias would be facilitated by different perspectives, expertise and experiences (i.e., diversity). While varying diversity on any number of dimensions (e.g., ethnic, gender, functional background, education, age) within teams has been studied in the literature (c.f., Kooij-de Bode, van Knippenberg and van Ginkel 2008; Williams and O’Reilly 1998; O’Reilly et al. 1998; Pelled, Eisenhardt and Xin 1999), research related to group performance has mixed reviews regarding the benefit of diversity within teams. While some diversity is thought to produce a more productive, functional conflict as opposed to an unproductive, relationship conflict (Jehn, Northcraft and Neale 1999), a meta-analysis on conflict (De Dreu and Weingart 2003) underscores that these various forms of conflict are all negatively related to group performance. Thus, group-level bias is included to assess potential issues associated with homogeneity within groups.

4.1.3 Evolutionary operators

Our model uses agent behaviors reflecting either selection or variation as analogues for decision making behavior: replication, random point mutation, intelligent point mutation, recombination, and subtractive selection. While these five operators reflect common forms of action in evolution (Mitchell 1996; Fogel 1995), they also align with actions commonly found in brainstorming and normative decision making idea generation phases where the goal is to build new ideas from individually generated suggestions (Paulus and Yang 2000) (i.e. mutations and recombination) and idea evaluation phases where culling or supporting ideas (i.e., replication and/or subtraction) leads to final group idea selection and decision. Among those evolutionary operators, replication and subtractive selection use a preferential random search algorithm (Solis and Wets 1981), where $r_p$ ideas are randomly sampled from the idea population in the agent’s mind and ranked according to their perceived utility values, and then the agent selects the best (or worst) idea for replication (or subtractive selection). Note that the designs of the evolutionary operators used in this model are different from those used in earlier models (Sayama and Dionne 2013a, Sayama and Dionne 2013b), in order to make the variation and selection mechanisms
more clearly separable. They are also extended so that their outcomes affect not only the agent’s own idea population but also those of its local neighbors on a social network, which represents the exchange of ideas through social ties. In other words, other agents can “hear” the focal agent’s opinion and update their own idea population according to it.

Replication selects an idea from the agent’s idea population with the above-mentioned preferential random search algorithm, and then adds an exact copy of the idea back to its own idea population, as well as to those of its local neighbors (i.e., other agents that are connected to the agent executing replication). Replication therefore can neither produce a novel idea nor remove one, but it gently sways the ecology of the population by increasing the popularity of favorable existent ideas within a local neighborhood in the social network. This represents an advocacy of a particular idea under discussion.

Random point mutation selects an idea from the population randomly, and then adds a copy of an idea with point mutations, flipping of bits at each aspect of a problem with a probability $p_m$, to the agent’s idea population as well as to those of its neighbors. This represents an attempt of making random changes to the existing ideas, reflected in asking “what if” questions. Random point mutations help escape local maxima of a utility function in the problem space when a utility function is nonlinear and many-peaked.

Intelligent point mutation selects an idea from the population randomly, makes several ($r_m$) tentative offspring of the idea by adding random point mutations, and selects that of the highest perceived fitness for addition to the population. The selected idea is added to the agent’s idea population as well as to those of its neighbors. This represents a proposal of an improved idea derived from an existing idea under discussion. The intelligent point mutation can be useful in maximizing a utility function with one maximum by climbing monotone gradients, but it may perform poorly in a complex utility landscape.

Recombination chooses two ideas from the agent’s idea population at random and then creates two offspring from the two parent ideas. Sexual reproduction is simulated with a multiple point cross-over recombination: parent ideas are aligned by aspects, for each of which there is a probability $p_s$ of switching their contents. Both of the two offspring are then added back to the agent’s idea population as well as to those of its neighbors. This represents a creation of new ideas from two existing ideas.

Finally, subtractive selection uses a negative preferential random search algorithm to find the idea with low fitness from the agent’s idea population, and then one copy of that idea is deleted from there, as well as from the idea populations of its neighbors (if a neighbor agent does not have a copy of the idea nothing will happen). This operator modestly reduces the popularity or importance of the idea within the local neighborhood in the social network. This represents a criticism against a bad idea. Subtractive selection is the only operator that reduces the number of existing ideas and is therefore essential to groups attempting to attain convergence in the population distribution.
Out of these five, replication and subtractive selection are selection-oriented operators, driving the exploitation in the discussion and decision making process. The other three (random/intelligent point mutations and recombination) are variation-oriented operators that increase the idea diversity and explore the problem space further. To systematically control and sweep the balance between the two evolutionary “forces” (selection/exploitation and variation/exploration), we introduced a global parameter $p$, which determines the behavioral tendency of agents. Specifically, each agent chooses an exploitative operator with probability $p$ (or, an explorative operator with probability $1 - p$; see Table 2). Setting $p = 1$ makes the agents completely selection-oriented, while $p = 0$ makes them fully exploratory.

### 4.1.4 Simulation settings

Table 2 summarizes the parameter values used in our computer simulations. Most of those values were taken from earlier work (Sayama and Dionne 2013a, Sayama and Dionne 2013b), and were chosen so as to be reasonable in view of typical real collective decision making settings. We tested several variations for each parameter value, confirming that the results were not qualitatively different from the ones presented below.

There are several experimental parameters that we varied in the three sets of experiments presented below. The first set of experiments manipulated $\beta$, group-level bias, and $\xi$, within-group noise. These two parameters were varied to represent different levels of accuracy and consistency of individual utility functions within a group. The second set of experiments varied $p$, the parameter that determines the balance between selection-oriented and variation-oriented operators in agents’ behaviors. The third set of experiments varied the size and topology of the group, by exponentially increasing the number of agents from $N = 5$, a small group whose size is within the optimal range for decision making teams (Kerr and Tindale, 2004; Salas, Stagl and Burke 2004), to $N = 640$, which forms a non-trivial social network. In all cases, the average node degree (i.e., average number of connections attached to a node) was always kept to four, which is a typical number of people one could have meaningful conversations with simultaneously. This assumption made the $N = 5$ case a fully connected network, while the network became increasingly sparse as $N$ increased. For each specific value of $N$, three different network topologies were tested: random (RD), small-world (SW; Watts and Strogatz 1998) and scale-free (SF; Barabási and Albert 1999). For small-world networks, the link rewiring probability was set to 10%, which realizes the small-world property (Watts and Strogatz 1998) for relatively small-sized networks like those used in this study. These topological variations do not cause any effective differences for smaller $N$, but as $N$ increases, their influences on network topology and dynamics of idea evolution begin to differentiate.

-----------------------------

Insert Table 2 Here
4.2 Metrics of group performance

Performance of a group is likely a multidimensional construct, as different authors have tested differing dimensions of group-based adaptation (c.f., LePine 2005; Kozlowski et al. 1999). For the purposes of collective decision making in organizational settings, the ability to converge on a decision is critical, as a group that cannot produce a decision likely fails in their task. In the meantime, convergence on a poor decision may be equally detrimental to a group as well, as mistakes could be costly. As such, it would seem that minimally the consideration of both convergence and decision quality would be needed to assess group performance. As required by increasingly complex organizational environments, groups and organizations need to converge quickly on decisions, and yet ensure these decisions have high efficacy related to solving perceived problems.

We therefore used two separate performance metrics: One was the true utility value of the mode idea (the most supported idea) in the final population of ideas collected from all the agents’ minds, to measure the overall quality of collective decisions. This was selected as it is most likely that the most supported idea represents the group’s preferred idea, and once selected, this supported idea will be tested in the context of real-world problem solving.

The other performance metric was the diversity of ideas remaining in the final population of ideas collected from all the agents’ minds, to measure the failure of the group to converge. This measurement is based on the classical definition of Shannon’s information entropy (Shannon 1948),

\[
H = - \sum_{i=1}^{m} p(x_i) \log_2 p(x_i),
\]

where \(m\) represents the number of different types of ideas in the final idea population, and \(p(x_i)\) is the ratio of the number of the \(i\)-th type of idea to the total size of the final idea population. The theoretical maximum of \(H\) would be \(M\), which occurs when all of \(2^M\) possible distinct ideas are equally represented. Since the entropy represents how many more bits would be needed to completely specify the single final collective decision, it can be assumed that \(M - H\) is a quantitative measure that intuitively means the number of aspects of the problem on which the group has formed a cohesive opinion. To rescale this to the range between 0 and 1, we used \((M - H) / M\) as a measurement of the convergence of final collective decision.

5 Results

5.1 Effects of within-group noise and group-level bias

We first conducted a computational experiment to examine the effects of increasing (a) within-group noise, \(\xi\), i.e., heterogeneity of individual utility functions within a group, and (b) group-level bias, \(\beta\), i.e., discrepancy of the master utility function from the true utility function at a group level, on the
overall group performance. For this experiment, the group was made of five agents with fully connected social network structure (i.e., everyone could talk to everyone else; a small group setting). We assumed that the agents were balanced in terms of their tendency between selection-oriented and variation-oriented behaviors in the discussion (i.e., \( p = 1/2 \)).

Figure 2 presents a summary of the results of simulations with within-group noise \( \xi \) and group-level bias \( \beta \) systematically varied. Each of the two performance metrics (i.e., level of convergence and utility of most supported idea, as described above) are visualized in a separate 3-D surface plot. We found that the level of convergence affected significantly by the within-group noise, while it was not affected at all by the group-level bias. On the other hand, the true utility of collective decisions degraded significantly when either the within-group noise or the group-level bias (or both) was increased. The true utility achieved by the most heterogeneous groups (\( \xi \sim 1.0 \)) or the most biased groups (\( \beta \sim 1.0 \)) dropped to about 0.5, which could be achieved just by random idea generation, meaning that there was no net improvement achieved during the discussion by those groups. This could be due to the within-group conflicts of interest (for greater \( \xi \)) and/or the lack of correct group-level understanding of the problem (for greater \( \beta \)).

In real-world settings, the within-group noise and the group-level bias are not independent from each other. More specifically, if a group is assembled by gathering similar individuals with similar backgrounds, expertise and opinions, then the group tends to have less within-group conflicts but may risk of having a greater group-level bias. On the other hand, if a group is made of diverse individuals with different backgrounds, expertise and opinions, the group may have greater within-group conflicts but it may successfully reduce potential group-level bias and accomplish deeper discussion and better integration of ideas, as the diverse perspectives may represent the true nature of the problem more correctly (we confirmed this observation by numerical tests; to conserve space, results are not shown here). Therefore, there is a trade-off between minimizing the within-group heterogeneity and the group-level bias in a realistic setting. What kind of strategies of group formation will be optimal in order to maximize the true utility of collective decisions remains a non-trivial and problem-dependent question.

5.2 Effects of balance between selection-oriented and variation-oriented behaviors

The “balanced” acts of agents assumed in the above experiment may be too ideal as a model of actual group members, because actual groups may have biased behavioral patterns as well. For example, some groups may be more prone to be critical, trying to purge bad ideas, while other groups may tend to promote combinations of multiple ideas in discussion. Examples of such behavioral patterns include
organizational “cultures” shared by all group members, which is a plausible view of a factor that may influence group dynamics (Salas et al. 2004).

We therefore ran another experiment to investigate the effects of balance between selection-oriented and variation-oriented behaviors patterns by systematically varying the parameter $p$. Greater values of $p$ represent groups with more selection-oriented behaviors (i.e., advocacy and criticism), while smaller values of $p$ represent groups with more variation-oriented behaviors (i.e., mutations and recombination). The group-level bias, $\beta$, was also varied as another experimental parameter, while the within-group noise, $\xi$, was fixed to 0.2 for this experiment. The group size and their network topology were the same as those in the first experiment.

Figure 3 shows a summary of the results of the second experiment comparing group performances with different group behaviors, plotting two performance metrics in separate 3-D plots as used for Figure 2 (note that one of the axes is now for $p$, not for $\xi$). The effect of behavioral balance on the level of convergence is straightforward in that greater $p$ (more selection-oriented behaviors) tended to promote convergence more. The effect of $p$ on the utility of collective decisions, however, turned out not so trivial. While purely variation-oriented behaviors ($p \sim 0.0$) did not help increase the decision quality, neither purely selection-oriented behaviors ($p \sim 1.0$) did. There was a range of optimal balance ($p = 0.7 \sim 0.9$) where the groups achieved the highest decision quality. In the meantime, the effect of group-level bias is similar to that seen in Figure 2, so that the utility of collective decisions would be significantly lower if there was group-level bias.

5.3 Effects of group size and social network topology

The first two experiments above assumed small, fully connected networks of agents. While their results produced useful implications for collective decision making in small group settings, they were not sufficient to generate insight into more general collective decision making dynamics on a larger nontrivial social environment, such as in a complex organization or on social media. We therefore conducted the third experiment in which the size of groups was increased from 5 to 640 in an exponential manner. For each size of the groups/networks, the average number of connections per agent (i.e., “degree” in network science terminology) were always kept to four, which was the same value as in the first two experiments above. The following values were used for other parameters: $\beta = 0.0$, $\xi = 0.2$, $p = 0.5$.

In this experiment, larger groups were no longer considered a typical “group”, but rather they formed a more complex social/organizational network, perhaps more indicative of a “collective” in the
organizational sciences. For each network size, we used the following three social network topologies. A new network topology was generated for each independent simulation run:

- **Random network** (RD): A random network is a network in which connections are randomly assigned, which can be used as a random control condition. For our experiment, a total of $2N$ links were established between randomly selected pairs of agents.

- **Small-world network** (SW; Watts and Strogatz 1998): A small-world network is a locally clustered (pseudo-)regular network, with a small number of global links introduced to reduce the effective diameter of the network significantly (i.e., a “small-world” effect). The small-world network may be considered a spatially extended network made of mostly local connections but with a few global connections. For our experiment, $N$ agents were first arranged in a circle and each agent was connected to its nearest and second nearest neighbors so that the degree would be four for all. Then 10% of the links were randomly selected and either the origin or destination of each of those links was rewired to a randomly selected agent.

- **Scale-free network** (SF; Barabási and Albert 1999): A scale-free network is a network in which the distribution of node degrees shows a power-law distribution. It represents a heterogeneous network made of a large number of poorly connected nodes and a few heavily connected “hubs”. Many real-world networks, including biological, engineered and social networks, were shown to be scale-free (Barabási 2009). While such networks show a small effective diameter like small-world networks, they may not have high local clustering. For our experiment, a well-known preferential attachment algorithm (Barabási and Albert 1999) was used, starting with a fully connected network of five agents and then incrementally adding an agent by connecting it with two links to two existing agents selected preferentially based on their degrees, until the network size reached $N$.

Figure 4 shows the effects of size and topology of networks on the decision outcomes. Without a surprise, the larger the group (or network) becomes, the harder it achieves convergence. Apparently there was no substantial difference between the three topological structures regarding their effects on the level of convergence. On the other hand, increasing group size had positive effects on the utility of the most supported idea within the group or on the social network. This can be understood in that, in a large network, agents can conduct different threads of discussions in parallel, which increases the chance for them to collectively find a better idea in the complex problem space. It is important for the agents to remain connected to each other so that the better ideas gradually spread over the network and widely accepted to become the more supported ideas. The same number of disconnected agents would not be able to achieve this kind of information aggregation and selection task.

-----------------------------
One particularly interesting phenomenon seen in Figure 4 is the difference in the utility of collective decisions between small-world networks and other two networks for larger $N$ ($N > 100$). Figure 5 provides a more detailed view into this finding, showing the distributions of utilities of most supported ideas for 500 independent simulation runs for $N = 640$ under each of the three conditions. In each condition, the agents were able to find the truly best idea with utility 1.0 most of the time, but small-world networks facilitated such optimal decision making most frequently. The Mann-Whitney $U$ test detected statistically significant differences between small-world and random ($p < 0.003$) as well as small-world and scale-free ($p < 10^{-6}$) networks, while there was no significant difference between random and scale-free ($p = 0.107$) networks. The key distinctive feature of small-world networks that are not present in either random or scale-free networks is the local clustering. Such locally clustered social network structure helps agents in different regions in a network maintain their respective focus areas and engage in different local search, possibly enhancing the effective parallelism of collective decision making and therefore resulting in a greater number of successful decisions. In contrast, random and scale-free networks lack such local clustering, and the links in those networks are all “global”, mixing discussions prematurely and therefore reducing the effective parallelism of collective decision making. These observations have an interesting contrast with the fact that random and scale-free networks are highly efficient in information dissemination because of their global connectedness. Our results indicate that such efficiency of information dissemination may not necessarily imply the same for collective decision making.

6 Conclusions
To improve our understanding of the dynamic nature of collective decision making, we developed an agent-based model and applied evolutionary operators as a means of illustrating how groups and collectives may move through a decision process based on ecologies of ideas over a social network habitat. Moreover, we considered various compositions of group members ranging from homogeneity to heterogeneity and examined the impact of team behaviors on the dynamic decision process as well. These explorations move toward a more realistic view of collective decision making within complex social systems, and answer calls (e.g., Meyer et al. 2005) for research that considers the impact of time and situations in flux, along with nonlinear, multi-level concepts incorporating evolutionary conceptual development.
Our exploration revealed that the composition of the team has implications for decision making and likely considers the complex nature of asking several individuals to come together and agree on a direction that is best suited for the group/collective, rather than for each individual. Research on group diversity has found mixed results related to diversity and group performance issues such as creativity and decision effectiveness (De Dreu and West 2001; Jackson 1992; Nemeth 1986; 1992; Hoffman 1979; Gruenfeld et al. 1996; Harrison et al. 2002; Jehn and Mannix 2001; O’Reilly et al. 1989; Kraiger and Ford 1985), however our research indicates an important trade-off between reduction of within-group conflicts and mitigation of group-level bias. This means that the best team composition may depend greatly on specific problem settings. For example, if a team is tasked to work on a time-critical mission, then the convergence speed is key to their success and thus the emphasis should be placed more on the group homogeneity to avoid within-group conflicts. Or, if a team is formed to seek a truly high quality solution to a problem, then minimizing the possibility of group-level bias is critical for the team’s success, which may require increasing within-group diversity.

Our results also imply that the balance between selection-oriented and variation-oriented behaviors may play an important role in collective decision making. While selection-oriented behaviors greatly promote convergence, they are not sufficient to achieve the highest possible utility. To improve the decision quality, the group also needs a good mixture of exploratory (variation-oriented) and exploitative (selection-oriented) behaviors. This also ties back to the diversity issue discussed above; a group may not necessarily benefit from diversity of individual problem understanding, but they can benefit from behavioral diversity of group members. In our simulations, the optimal balance between selection and variation was attained at $p \sim 0.8$ (i.e., 80% selection, 20% variation) but this particular balancing point may be problem dependent.

Our results with social network structure illustrated intriguing effects of network topologies on decision quality, which was manifested particularly for larger networks. Small-world networks with spatially localized clusters tended to promote collective search of optimal ideas more often than random or scale-free networks, despite that the network size and the average degree were all identical. This finding offers another implication for the diversity in collective decision making: certain organizational structures may be more effective in generating and maintaining idea diversity in discussion, while other structures would tend to reduce idea diversity and promote premature convergence on suboptimal ideas more often. This is similar to the biological fact that certain geographical habitat structures can maintain greater biodiversity in evolutionary ecology. In the decision making context, this implies that not only within-group diversity or behavioral balance but also social network topologies could influence the dynamics of idea evolution in collective decision making processes.
Using an evolutionary framework to model collective decision making processes, one can specifically examine the efficacy of a variety of decision processes employed by groups and collectives. The framework enables a means for direct comparison of various idea evolution paths within collective decision making, and enables an exploration of how the make-up and structure of teams could be critical depending on the overall requirements for decision making tasks.

Furthermore, the evolutionary framework and subsequent computational model enables advancements in understanding collective decision making within a dynamic and complex social system. By employing an evolutionary framework we can explore the impact of time and situations in flux, and the modeling enables nonlinear exploration of processes. Finally, the multi-level, network-oriented nature of the research more appropriately models the potential differences in team composition and organizational topologies. This research adds to our understanding of the complex nature of collective decisions, and the potential pitfalls and caveats of employing various decision processes and designing teams in a heterogeneous and/or homogeneous manner.

There are several limitations to our modeling study. For example, genetic operators may not exist in groups as “cleanly” as modeled in our simulation. We used simple parameterized settings to control the prevalence of operators, which may not be appropriate to represent the real human individual behavior in discussion. Also, our model considered only the heterogeneity of the utility functions of agents. In real human systems, the heterogeneity, or diversity, implies far richer concepts (Dionne et al. 2004), such as different backgrounds, professional expertise, and behavioral strategies, which were not present in our current model. To conduct a more comprehensive, systematic investigation of the homogeneity/heterogeneity issues, it would be critical to incorporate the heterogeneity of the participants’ domains of expertise, in addition to their utility functions. Having team members with diverse domains of expertise may further improve group performance. Furthermore, we tested only three typical social network topologies, but they are by no means an exhaustive list of possible organizational structures. Conducting experiments on more realistic social network topologies would add more realistic dynamics to the results.

Computer simulations provide a mechanism to study complex, dynamic collective processes with relatively little cost to researchers and “subjects”, yet no level of model complexity could adequately capture the complexity of navigating decision making in real group environments (Adner et al. 2009). The interactive effects of levels of analysis, personality, knowledge, learning, group dynamics and the environment will likely remain the most complex of models. As such, to refine theory and direct and pinpoint empirical research, simulation is an excellent “first responder.” To offer practical ideas to organizations, group members and leaders, however, research needs to be conducted in such a way as to capture and analyze the actions of real groups, and assess theoretical hypotheses against empirical
findings. Our simulations findings here could serve as a basis or direction for future experimental and field studies of decision making in various types of heterogeneous and homogeneous real-world groups and collectives.

Acknowledgments: Research supported by the National Science Foundation (SES-0826711)
References

Abbot A (2001) Time Matters. University of Chicago Press, Chicago, Il

Adner R, Polos L, Ryall M, Sorenson O (2009) Introduction to special topic forum: The case for formal theory. Acad Management Rev 34: 201-208

Axelrod R (1981) The evolution of cooperation. Sci 211: 1390-1396

Barabási AL, Albert R (1999) Emergence of scaling in random networks. Science 286: 509-512.

Barabási AL (2009) Scale-free networks: a decade and beyond. Science 325: 412-413.

Bar-Yam Y (1997) Dynamics of complex systems. Westview Press, Boulder, CO

Bar-Yam Y (2004) Making things work: Solving complex problems in a complex world. NESCI Knowledge Press, Cambridge, MA

Battiston S, Bonabeau E, Weisbuch G (2003a) Decision making dynamics in corporate boards. Physica A 322: 567-582

Battiston S, Weisbuch G, Bonabeau E (2003b) Decision spread in the corporate board network. Adv Complex Systems 6: 631-644

Carroll T, Burton RM (2000) Organizations and complexity: Searching for the edge of chaos. Comput Math Organ Theory 6: 319-337

Chang MH, Harrington JE Jr (2007) Discovery and diffusion of knowledge in an endogenous social network. Amer J Sociol 110(4): 937-976

Chang MH, Harrington JE Jr (2005) Innovators, imitators and the evolving architecture of problem-solving networks. Organ Sci 18(4): 648-666

Dansereau F, Alutto JA, Yammarino FJ (1984) Theory Testing in Organizational Behavior: The Varient Approach. Prentice-Hall, Englewood Cliffs, NJ
Dansereau F, Yammarino FJ, Kohles J (1999) Multiple levels of analysis from a longitudinal perspective: Some implications for theory building. Acad Management Rev 24: 346-357

De Dreu CKW, Weingart LR (2003) Task and relationship conflict, team performance, and team member satisfaction: A meta-analysis. J Appl Psych 88: 741–749

De Dreu CKW, West MA (2001) Minority dissent and team innovation: The importance of participation in decision making. J Appl Psych 86: 1191-1201

Dionne SD, Akaishi J, Chen X, Gupta A, Sayama H, Yammarino FJ, Serban A, Hao C, Head HJ, Bush BJ (2012) Retrospective Relatedness Reconstruction: Applications to Adaptive Social Networks and Social Sentiment. Organ Res Methods 15(4): 663-692

Dionne SD, Dionne PJ (2008) Levels-based leadership and hierarchical group decision optimization: A simulation. Leadership Quart 19: 212-234

Epstein JM (2006) Generative Social Science: Studies in Agent-based Computational Modeling. Princeton University Press

Epstein JM, Axtell R (1996) Growing Artificial Societies: Social Science from the Bottom Up. Brookings Institute Press, Washington, DC.

Fogel DB (1995) Evolutionary Computation: Toward a New Philosophy of Machine Intelligence. IEEE Press, Piscataway, NJ

Futuyma DJ (2005) Evolution. Sinauer Associates, Sunderland, MA

Gavetti G, Daniel A Levinthal DA (2000) Looking Forward and Looking Backward: Cognitive and Experiential Search, Administrative Sci Quart 45: 113 – 137

Gilbert N, Troitzsch KG (1999) Simulation for the social scientist. Milton Keynes: Open University Press
Gigone D, Hastie R (1993) The common knowledge effect: Information sharing and group judgment. J Personality Soc Psych 65: 959-974

Gruenfeld DH, Mannix EA, Williams KY, Neale MA (1996) Group composition and decision making: How member familiarity and information distribution affect process and performance. Organ Behavior Human Decision Processes 67: 1-15

Hamming RW (1950) Error detecting and error correcting codes. Bell System Tech J 26: 147-160

Harrison DA, Price KH, Gavin JH, Florey AT (2002) Time, teams, and task performance: Changing effects of surface-level and deep-level diversity on group functioning. Acad Management J 45: 1029-1045

Hoffman LR (1979) Applying experimental research on group problem solving to organizations. J Appl Behavioral Sci 15: 375-391

Hollenbeck JR, Ilgen DR, Sego DJ, Hedlund J, Major DA, Phillips J (1995) Multilevel theory of team decision making: Decision performance in teams incorporating distributed expertise. J Appl Psych 80(2): 292-316

Horst R, Pardalos PM, Thoai NV (2000) Introduction to Global Optimization, 2nd edn. Kluwer Academic Publishers, Dordrecht, Netherlands

Jackson S (1992) Team composition in organizations. In: Worchel S, Wood W, Simpson J (eds) Group Process and Productivity. Sage Publications, London

Jehn KA, Mannix EA (2001) The dynamic nature of conflict: A longitudinal study of intragroup conflict and group performance. Acad Management J 44: 238-251

Jehn KA, Northcraft GB, Neale MA (1999) Why differences make a difference: A field study of diversity, conflict, and performance in workgroups. Admin Sci Quart 44: 741–763

Kauffman SA (1993) The origin of order. Oxford University Press, NY

Kerr NL, Tindale RS (2004) Group performance and decision making. Ann Rev Psych 55: 623-655
Klein M, Sayama H, Faratin P, Bar-Yam Y (2003a) The dynamics of collaborative design: Insights from complex systems and negotiations research. Concurrent Engrrg: Res Appl 11: 201-209

Klein M, Faratin P, Sayama H, Bar-Yam Y (2003b) Protocols for negotiating complex contracts. IEEE Intelligent Systems 18(6): 32-38

Klein M, Faratin P, Sayama H, Bar-Yam Y (2006) An annealing protocol for negotiating complex contracts. In: Rennard J-P(ed) Handbook of Research on Nature Inspired Computing for Economics and Management, vol 2. Idea Group Publishing, Hershey, PA, Chapter XCVIII

Klein KJ, Dansereau F, Hall RJ (1994) Levels issues in theory development, data collection, and analysis. Acad Management Rev 19: 195-229

Knudsen T, Levinthal DA (2007) Two faces of search: Alternative generation and alternative evaluation. Organ Sci 18(1): 39-54

Kock N (1999) Process Improvement and Organizational Learning: The Role of Collaboration Technologies. Idea Group Publishing, Hershey, PA

Kock N (2004) The psychobiological model: Towards a new theory of computer-mediated communication based on Darwinian evolution. Organ Sci 15(3): 327-348

Kooij-de Bode HJM, van Knippenberg D, van Ginkel WP (2008) Ethnic diversity and distributed information in group decision making: The importance of information elaboration. Gr Dyn: Theory Res Pract 12: 307–320

Kozlowski SWJ, Gully SM, Nason ER, Smith EM (1999) Developing adaptive teams: A theory of compilation and performance across levels and time. In: Ilgen DR, Pulakos ED (eds) The Changing Nature of Performance: Implications for Staffing, Motivation and Development. Jossey-Bass, San Francisco, CA, pp 240-292

Kraiger K, Ford JK (1985) A meta-analysis of ratee-race effects in performance ratings. J Appl Psych 70: 56-65
LePine JA (2005) Adaptation of teams in response to unforeseen change: Effects of goal difficulty and team composition in terms of cognitive ability and goal orientation. J Appl Psych 90: 1153-1167

Levinthal DA (1997) Adaptation on rugged landscapes. Management Sci 43(7): 934-950

Lightle JP, Kagel JH, Arkes HR (2009) Information exchange in group decision making: The hidden profile problem reconsidered. Management Sci 55(4): 568-581

Lipshitz R, Klein G, Orasanu J, Salas E (2001) Focus Article: Taking stock of naturalistic decision making. J Behavioral Decision Making 14: 331-352

Maldonato M (2007) Undecidable decisions: Rationality limits and decision-making heuristics. World Futures: J General Evolution 63(1): 28-37

Mannes AE (2009) Are we wise about the wisdom of crowds? The use of group judgments in belief revision. Management Sci 55(8): 1267-1279

March JG (1991) Exploration and exploitation in organizational learning. Org Sci 2: 71-87.

Meyer AD, Gaba V, Colwell KA (2005) Organizing far from equilibrium: Nonlinear change in organizational fields. Organ Sci 16(5): 456-473

Miller JH, Page SE (2007) Complex Adaptive Systems: An Introduction to Computational Models of Social Life. Princeton University Press, Princeton, NJ

Mitchell M (1996) An Introduction to Genetic Algorithms. MIT Press, Cambridge, MA

Mitchell M, Forrest S, Holland JH (1991) The royal road for genetic algorithms: Fitness landscapes and GA performance. In: Varela FJ, Bourgine P (eds) Toward a Practice of Autonomous Systems: Proceeds of the First European Conference on Artificial Life. Paris, France, pp 245-254

Nemeth CJ (1986) Differential contributions of majority and minority influence. Psych Rev 93: 23-32
Nemeth CJ (1992) Minority dissent as a stimulant to group performance. In: Worchel S, Wood W, Simpson J (eds) Group Process and Productivity. Sage Publications, London, pp 95-111

Nijstad BA, Kaps SC (2007) Taking the easy way out: Preference diversity decision strategies and decision refusals in groups. J Personality Soc Psych 94(5): 860-870

O’Reilly CA, Caldwell DF, Barnett WP (1989) Work group demography, social integration and turnover. Admin Sci Quart 34: 21-37

O’Reilly CA, Williams KY, Barsade S, Gruenfeld DH (1998) Group Demography and Innovation: Does Diversity Help? In M. A. Neale & E. A. Mannix (Ed), Research on Managing Groups and Teams Vol. 1: 183-207

O’Reilly T (2005) What is Web 2.0: Design patterns and business models for the next generation of software. IOP O’Reilly. http://www.oreillynet.com/pub/a/oreilly/tim/news/2005/09/30/what-is-web-20.html. Accessed October 8, 2012

Paulus PB, Yang H-C (2000) Idea generation in groups: A basis for creativity in organizations. Organ Behavior Human Decision Processes 82: 76-87

Pelled LH, Eisenhardt KM, Xin KR (1999) Exploring the black box: An analysis of work group diversity, conflict and performance. Admin Sci Quart 44:1-28

Ren Y, Carley KM, Argote L (2006) The contingent effects of transactive memory: When is more beneficial to know what others know? Management Sci 52: 671-682

Rivkin JW (2000) Imitation of complex strategies. Management Sci 46(6): 824-844

Rodriguez, MA, Steinbock DJ (2004) A social network for societal-scale decision making systems. In NAACSOS 2004: Proc North Amer Association Comput Soc Organ Sci Conf, Pittsburgh, PA

Rusmevichientong P, Van Roy B (2003) Decentralizing decision making in a large team with local information. Games Econom Behavior 43: 266-295
Salas E, Klein G (2001) Expertise and naturalistic decision making: An overview. In: E. Salas E, Klein G (eds) Linking Expertise and Naturalistic Decision Making. Lawrence Erlbaum Associates, Philadelphia, PA, pp 3-33

Salas E, Stagl KC, Burke CS (2004) 25 years of team effectiveness in organizations: Research themes and emerging needs. In: Cooper CL, Robertson IT (eds) International Review of Industrial and Organizational Psychology 19: 47-91

Sayama H, Dionne SD (2013a) Using evolutionary computation as models/tools for human decision making and creativity research. Proc 4th IEEE Symp Artif Life, pp.35-42.

Sayama H, Dionne SD (2013b) Studying collective human decision making and creativity with evolutionary computation. Under review.

Sayama H, Farrell DL, Dionne SD (2011) The effects of mental model formation on group decision making: An agent-based simulation. Complexity 16(3): 49-57.

Shannon CE (1948) A mathematical theory of communication. Bell System Tech J 27: 379-423

Simon HA (1955) A behavioral model of rational choice. Amer Econom. Rev 69: 99-118

Silverman BG, Johns M, Corwell J, O’Brien K (2006) Human behavior models for agents in simulation games: Part 1: Enabling science with PMFserv. Presence 15(2): 139-162

Solis FJ, Wets, RJ-B (1981) Minimization by random search techniques. Math Oper Res 6: 19-30

Stasser G, Stewart D (1992) Discovery of hidden profiles by decision making groups: Solving a problem versus making a judgment. J Personality Soc Psych 57: 67-78

Stasser G, Titus W (1985) Pooling of unshared information in group decision making: Biased information sampling during discussion. J Personality Soc Psych 48: 1467-1478

Sterman JD (2000) Business dynamics: System thinking and modeling for a complex world. Irwin McGraw Hill, Boston, MA
Van de Ven A, Delbecq AL (1974) The effectiveness of nominal, delphi, and interacting group decision making processes. Acad Management J 117: 605-621

van Ginkel WP, van Knippenberg D (2008) Group information elaboration and decision making: The role of shared task representations. Org Behavior Human Decision Processes 105(1): 89-97

Watts DJ, Strogatz SH (1998) Collective dynamics of ‘small-world’ networks. *Nature* 393: 440-442

Williams KY, O’Reilly CA (1998) Demography and diversity in organizations. Res Organ Behavior, 20: 77–140

Wilson DS (2005) Evolution for everyone: How to increase acceptance of interest in, and knowledge about evolution. Public Library Sci Biol 3(12): e364

Wilson DS, Wilson EO (2008) Evolution for the “good of the group.” Amer Sci 96: 380-389

Yamanoi J, Sayama H (2012) Post-merger cultural integration from a social network perspective: A computational modeling approach. Comput Math Org Theory 18: 1-22

Yammarino FJ, Dansereau F (eds) 2002 The many faces of multi-level issues. Research in Multi-Level Issues, vol 1. Elsevier Science, Oxford, UK

Yammarino FJ, Dansereau F (2011) Multi-level issues in evolutionary theory, organization science, and leadership. Leadership Quart 22: 1042-1057

Yammarino FJ, Dionne SD, Chun JU, Dansereau F (2005) Leadership and levels of analysis: A state-of-the-science review. Leadership Quart 16: 879-919
TABLE 1
Evolutionary Concepts Applied to Corresponding Decision Making Process Components

| Evolutionary Concept                  | Decision Making Component                                                                 |
|--------------------------------------|-------------------------------------------------------------------------------------------|
| Genetic possibility space             | Problem space (decision space)                                                            |
| Genome                               | Potential idea (a set of choices for all aspects of the problem)                          |
| Locus on a genome                    | Aspect of the problem                                                                     |
| Allele (specific gene) on a locus     | Specific choice made for an aspect                                                        |
| Population                           | A set of potential ideas being discussed                                                  |
| Fitness                              | Utility value of a potential idea (either perceived or real)                               |
| Adaptation                           | Increase of utility values achieved by an idea population                                   |
| Selection                            | Narrowing of diversity of ideas based on their fitness                                     |
| Replication                          | Increase of relative popularity of a potential idea in the discussion                     |
| Recombination                        | Production of a new potential idea by crossing multiple ideas                              |
| Mutation                             | Point-like change in an idea (possibly coming up with a novel idea)                       |
### TABLE 2

**Parameters and Symbols**

(Bold indicates experimental parameters varied)

| Parameter                          | Value | Meaning                                                                 |
|------------------------------------|-------|-------------------------------------------------------------------------|
| **Parameters Related to Evolutionary Decision Process** |       |                                                                         |
| $M$                                 | 10    | Problem space dimensionality                                            |
| $n$                                 | 10    | Number of representative ideas to generate true/master utility functions |
| $r_p$                              | 5     | Number of sample ideas in preferential search algorithm                 |
| $r_m$                              | 5     | Number of offspring generated in intelligent point mutation            |
| $p_m$                              | 0.2   | Random mutation rate per bit                                            |
| $p_s$                              | 0.4   | Probability of random switching in recombination                       |
| $p$                                | 0~1   | Probability for an agent to take selection-oriented actions             |
| $p/2$                              |       | Probability of replication - advocacy (increases popularity; selection-oriented) |
| $p/2$                              |       | Probability of subtractive selection - criticism (decreases popularity; selection-oriented) |
| (1-$p$)/3                          |       | Probability of random point mutation - minor modification of idea (variation-oriented) |
| (1-$p$)/3                          |       | Probability of intelligent point mutation - improvement of existing idea (variation-oriented) |
| (1-$p$)/3                          |       | Probability of recombination - generating new ideas from crossing multiple existing ideas (variation-oriented) |
| **Parameters Related to Team Characteristics** |       |                                                                         |
| $N$                                | 5~640 | Size of group/social network                                            |
| **Network topology**               | RD, SW, SF | RD: random network, SW: small-world network, SF: scale-free network |
| $d$                                | 4     | Average degree (average number of links connected to each agent)        |
| $k$                                | 5     | Number of initial randomly generated ideas in each agent’s mind         |
| $\beta$                            | 0~1   | Group-level bias                                                        |
| $\xi$                              | 0~1   | Within-group noise                                                      |
| $T$                                | 60    | Number of iterations                                                    |
FIGURE 1

Master and Individual Utility Functions

Note:
The master utility function with $M = 10$, generated from a representative set of idea utilities of size $n = 10$, is shown by black dots. An individual utility function by adding noise with $\xi = 0.2$ is shown by gray dots. The $x$-axis shows idea indices generated by interpreting bit strings as binary notations of an integer, i.e., all of different ideas are lined up along the horizontal axis and their utility values are plotted. It can be seen in the figure that the perturbed individual utility function (gray dots) maintains some structures of the master utility function (black dots), but they are not exactly the same, which represents the misunderstanding of the problem by the individual.
FIGURE 2

Effects of Within-Group Noise and Group-Level Bias on Decision Convergence and Decision Quality

Note:
These plots summarize simulation results showing the effects of within-group noise ($\xi$) and group-level bias ($\beta$) on the level of convergence (left) and the true utility value of the most supported idea (right). Each dot represents an average result of 500 independent simulation runs. Left: Decision convergence was high when within-group noise was small, i.e., when groups were homogeneous in terms of the agents’ individual utility functions. Group-level bias did not show any substantial effect on decision convergence. Right: Quality decisions were made only if both within-group noise and group-level bias were small. As either increases, the quality of the most supported idea decreases.
FIGURE 3

Effects of Balance between Selection-Oriented and Variation-Oriented Behaviors and Group-Level Bias on Decision Convergence and Decision Quality

Note:
These plots summarize simulation results showing the effects of group-level balance between selection-oriented and variation-oriented behaviors ($p$) and group-level bias ($\beta$) on the level of convergence (left) and the true utility value of the most supported idea (right). Each dot represents an average result of 500 independent simulation runs. Left: Decision convergence was high when group-level behavior was highly selection-oriented ($p \sim 1$), i.e., when groups used replication (advocacy) and subtractive selection (criticism) most of time. Group-level bias did not show any substantial effect on decision convergence. Right: Quality decisions were made only if the group-level behavior was maintained at an optimal balance between selection-oriented and variation-oriented behaviors ($p = 0.7\sim0.9$) while group-level bias was small.
FIGURE 4

Effects of Group Size and Social Network Topology on Decision Convergence and Decision Quality

Note:
These plots summarize simulation results showing the effects of group size (N) and social network topology (random, small-world or scale-free) on the level of convergence (left) and the true utility value of the most supported idea (right). Note the log scale for group size. Each dot represents an average result of 500 independent simulation runs. Left: Decision convergence decreased as the group size increased. Social network topology did not influence decision convergence very much. Right: For smaller groups (N < 100), the topological difference between random, small-world and scale-free networks did not have substantial effects, but for larger groups (N > 100), the small-world topology outperformed the other two topologies in terms of the quality of the most supported idea.
FIGURE 5

Comparison of Distributions of Utilities of Most Supported Ideas Between Different Social Network Topologies

Note:
These plots summarize simulation results comparing the distributions of utilities of most supported ideas at the end of simulation between the three social network topologies (random, small-world or scale-free) for $N = 640$. The small-world network topology (middle) achieved the highest number of the maximal utility value (1.0) compared to the other two topologies, random (left) and scale-free (right). The Mann-Whitney $U$ test revealed that there was a statistically significant difference between small-world and the other two (small-world v. random: $p < 0.003$, small-world v. scale-free: $p < 10^{-6}$), while there was no statistically significant difference between random and scale-free topologies ($p = 0.107$).