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Research Article

Group Size and Group Performance in Small Collaborative Team Settings: An Agent-Based Simulation Model of Collaborative Decision-Making Dynamics

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The relationship between size and performance of collaborative human small groups has been studied broadly across management, psychology, economics, sociology, and engineering disciplines. However, empirical research findings on this question remain equivocal. Many of the earlier studies centered on empirical human-subject experiments, which inevitably involved many confounding factors. To obtain more theory-driven mechanistic explanations of the linkage between group size and performance, we developed an agent-based simulation model that describes the complex process of collaborative group decision-making on problem-solving tasks. To find better solutions to a problem with given complexity, these agents repeatedly explore and share solution candidates, evaluate and respond to the solutions proposed by others, and update their understanding of the problem by conducting individual local search and incorporating others' proposals. Our results showed that under a condition of ineffective information sharing, group size was negatively related to group performance at the beginning of discussion across each level of problem complexity (i.e., low, medium, and high). However, in the long run, larger groups outperformed smaller groups for the problem with medium complexity and equally well for the problem with low complexity because larger groups developed higher solution diversity. For the problem with high complexity, the higher solution diversity led to more disagreements which in turn hindered larger groups' collaborative problem-solving ability. Our results also suggested that, in small collaborative team settings, effective information sharing can significantly improve group performance for groups of any size, especially for larger groups. This model provides a unified, mechanistic explanation of the conflicting observations reported in the existing empirical literature.

1. Introduction

Collective decision-making is ubiquitous in social systems, such as juries in the court [1, 2], political parties [3], sports teams [4], and committees of specialists [5]. Group composition is critical to collective decision-making processes and outcomes [6–8]. Research on group composition has demonstrated promising achievements in diverse topics, from demographic diversity [9–11], personality [12–14] to cognitive ability [15, 16], and social status [17, 18]. However, research on group size, as an important field in group composition, failed to establish a definitive conclusion regarding the ideal group size for the highest group performance. Some empirical research suggested that group size was negatively related to group performance, because of social loafing [19–22], poor group communication [23–25], and difficulty in coordination [26, 27]. Other studies reported a positive relationship between group size and group performance [28–30] as larger groups were able to get access to more resources, perspectives, and expertise. Meanwhile, some research concluded that group size had a curvilinear relationship with group performance such that having too few or too many members would reduce performance [31–33] because small groups might lack the diversity of perspectives, whereas larger groups tended to divide into subgroups which would hinder group outcomes. Some empirical studies even found the group size to be unrelated to group performance [34, 35].

Most of the reported research linking group size to group performance centered on human-subject experiments, which were limited in experimental settings, quantifying task complexity, measuring temporal dynamics of group interactions, and monitoring information transmission (or sharing) within a group. However, these factors are critical to collective decision-making and may also impact the experimental observations regarding group size and group performance. Task complexity has been demonstrated to be negatively related to group performance [36, 37]; meanwhile, groups of different sizes differed in performance on simple tasks and more complex tasks [38]. Most of those experimental studies were mainly based on simplified tasks (e.g., rope pulling [22], clapping and shouting [25], undemanding paperwork processing [29], or simple brainstorming [34]) as testing specific theoretical hypotheses necessitated the exclusion of unrelated confounding factors. A few empirical studies considered more complex tasks [28, 38], yet they did not quantify the exact complexity of the given tasks. Time is also a critical factor that cannot be neglected in collective decision-making because groups can learn and evolve [39]. The group mental models and the group performance can also change over time [40, 41]. Experiments related to group size and performance were generally completed in a limited time, which ignored the process from group formation to maturation [39, 42]. Finally, information transmission (or sharing) can reduce group conflicts, enhance group understanding, and improve consensus in groups [43, 44], which is crucial but difficult to observe or control in experiments. Therefore, these experimental limitations may lead to a large bias in the research regarding the relationship between group size and group performance.

In an effort to address these issues in lab or online experimental studies, researchers have developed many computational models regarding group research, such as group development [45–48], group effectiveness and enhancements [49–53], information transmission [54, 55], and leadership [56–58]. However, little modeling and simulation research has explored the relationship between group size and group performance.

To address the aforementioned limitations in the empirical studies, we developed a mechanistic agent-based model to theoretically explore the relationship between group size and group performance, aiming at providing a unifying explanation that can connect those conflicting empirical observations reported in human-subject experiments. In our model, the agents act with bounded rationality: each agent always makes the most logical, rational choices using its own knowledge about the problem, but it is not omniscient about the whole problem due to limited information and potential knowledge biases. Using this model, we examine the impact of task complexity, discussion time, and information sharing on the process of collaborative group decision-making. Our simulation results revealed that the relationship between group size and performance varied depending on task complexity, discussion time, and ways of information sharing. Most of the reported experimental observations can be explained by our simulation results.

Many types of modeling techniques have been successfully used to model and analyze collaborative decision-making problems, such as agent-based modeling and simulation (ABMs) [59], companion modeling (ComMod) [60], and differential equation-based models [61]. In this work, we chose the ABMs because they are straightforward, powerful, and flexible in describing complex interactions among discrete individuals. Furthermore, ABMs can capture emergent phenomena from a microscopic level to a macroscopic level in complex systems (e.g., human groups) and provide a natural, interpretable description of a social system. Many applications of ABMs range from modeling agent behavior in the stock market, human groups, and consumer markets to disease spread and the development of biowarfare [62].

2. Model Description

The model simulates real-world collaborative problem-solving in human groups that can be characterized as a sequential search process [63, 64]. In the search process, group members are directed at finding solutions that are superior to those currently known. Based on this type of search process, the model considers a small group consisting of a specific number of interacting agents attempting to search for the optimal solution to a given problem space. Each agent tries to navigate the group discussion according to its own knowledge of the problem. The collaborative

decision-making process is modeled as a sequence of iterative group discussion actions on the problem space, which consists of five phases: (1) individual local search, (2) selection of a speaker, (3) proposal of a new solution by the speaker, (4) evaluation and response to speaker's proposal by the listeners, and (5) the overall response to the proposal at the group level. Group members are assumed to be equally located in a complete social network (i.e., each member can interact with any other members). Note that these assumptions are not applicable to large-scale groups because large-scale groups often tend to decompose into small clusters [65] or be organized in a structured organization [66].

The details of the agent-based model are described below, which follows the ODD (Overview, Design concepts, Details) protocol [67]. The hardware and software used in this work are shown in Table 1. The codes for this model are available from https://github.com/shun-cao/Agent-based-model-for-group-size-and-performance.

2.1. Purpose.
The purpose of our model is to study the effects of time and task complexity on the relationship between group size and performance in small group settings. The model does not realistically replicate any empirically real-world collaborative group process but instead aims at revealing how group size affects group performance in distinct situations based on some simplified observations and reasonable assumptions.

2.2. Entities, State Variable, and Scales.
The entities of the model include problem spaces and agents that represent the tasks and the group members, respectively. The temporal scale is set as hours because collective decision-making duration is often counted in working hours. Every time step (i.e., every iteration) in computer simulation represents a discussion round of a group. The state variables in this model include *agent current solution* and the corresponding utility, *agent memory*, agent *individual utility function*, *group solution* and the corresponding utility, and the *ratio of agreement* in each discussion round. The detailed description of entities and state variables is as follows. Table 2 lists all the state variables in this work.

2.2.1. Problem Space (Entity).
The problem space is defined as a tunable rugged space with interdependencies among distinct dimensions. Each possible combination of choices is represented by one point on the problem space, while the height of each point represents the utility value of that combination. The problem space incorporates multiple peaks and valleys characterized by higher and lower utilities, respectively. Roughly speaking, the complexity of the problem space can be characterized by the number of peaks and valleys. Searching for better solutions in this type of problem space may indicate the creation of strategies in business, the development of new products, the design thinking process, the seeking scientific truth in nature, etc., which require considering multiple interdependent aspects

Table 1: Configuration of the experimental platform.

Hardware	
CPU: 2.3 GHz Intel Core i5	
Memory: 8 GB 2133 MHz LPDDR3	
Software	
OS: macOS Sierra version 10.12.6	
Editor: PyCharm 2020.1.5 (community edition)	
Python: Python 3.7	

of the problems/projects simultaneously. Correspondingly, the utility value of a solution represents the quality of a strategy, a developed product, a new design, or research finding, etc.

Mathematically, the problem space is defined on a discrete space, $S = [0, 1/n, \ldots, n - 1/n, 1]^m$, where m is a positive integer representing the dimensions of the problem space, while n determines the number of choices in each dimension. Each point in the space denotes one solution for the problem. Thus, there are total $(n + 1)^m$ possible solutions in the problem space. Each solution has a utility that represents its quality (the higher the better). The assignment of utility values over the problem space is defined in the following way.

First, h representative solutions $H = \{v_i \mid i = 1, \ldots, h\}$ are randomly generated and assigned a utility value randomly selected from $Q = \{j/q \mid j = 1, \ldots, q - 1\}$ with selection probability $P(j/q) = 1 - (j/\sum_1^{q-1} j)$, where q is a constant. The quantity of representative solutions decides (not equals to) the number of peaks and valleys in the problem space, which is used as a tunable parameter for various complexity of the problem space. This utility assignment assures that solutions with higher utility are few, whereas solutions with lower utility (including valleys) are many, which assures there is only one optimal solution and the distance between optimal and suboptimal solutions is large enough in the problem space. This gives room for comparing the performances of distinct groups in various situations. Second, to make sure the range of the utility over the problem space is [0, 1], we randomly choose one solution with minimum utility and the other one with maximum utility from H and replace their utilities with 0.0 and 1.0, respectively. Third, the true utility function of the problem space is defined over its whole domain by interpolation using these H solutions and the corresponding utility values:

$$U_T(v) = \frac{\sum_{i=1}^h U_T(v_i) D(v_i, v)^{-2}}{\sum_{i=1}^h D(v_i, v)^{-2}}, \tag{1}$$

where $v \notin H$ is a solution for the problem, $U_T(v_i)$ is the utility value of the representative solution $v_i \in H$, and $D(v_i, v)$ is the Euclidean distance between v_i and v. The second and third steps of the definition of the problem space are based on prior work [52, 56]. Formula (1) represents a simple interpolating algorithm that computes a weighted average of initially generated utility values ($U_T(v_i)$) using normalized inverse square distances between initially generated solutions v_i and a solution in question v. The designed problem space in this work can be seen as a simple version of the NK model that uses simulation methods to construct

TABLE 2: Summary of state variables in our model.

State variable	Variable type	Description
Agent memory	A set including multiple vectors	Agent memorized solutions, each of them is a vector (i.e., a point on a problem space)
Agent current solution	A vector	The best solution in the agent's memory
Utility of agent current solution	A real number between 0.0 and 1.0	The utility of the agent's current solution
Agent individual utility function	A formula based on given vectors and a vector in question	It gives an agent's representation of a given problem space
Group solution	A vector	A group's current solution
Utility of group solution	A real number between 0.0 and 1.0	The utility of a group's current solution
Ratio of agreement	A real number between 0.0 and 1.0	It represents group consensus on a proposed solution

performance landscapes and examine various aspects of the effective search process [68]. This type of rugged landscape has been widely used as a searching space in studies of management, business, social science, biology, engineering, etc. [69]. Note that the problem space is not directly accessible to any agent.

2.2.2. Agents (Entity).
Each agent is assumed to have the same participation rate and own the same social status. Additionally, there are no assigned roles (e.g., leaders, mediators, etc.) in a group. Each agent is designed to have a memory capacity c, which means it can memorize c solutions and corresponding utilities at most. Each agent also has an individual utility function as a personal representation of a problem space, which decides the agent's independent searching direction and its evaluation of others' proposals.

2.2.3. Agent Memory (State Variable).
Each agent has a memory that can incorporate (memorize) as many as c solutions and those corresponding utilities over the group process. Solutions in agent i's memory are denoted as $M_i^v = \{v_{ij} | j = 1, \ldots, k | k \le c\}$, where v_{ij} and k are the agent i's j_{th} solution and the number of solutions in its memory, respectively. The corresponding utilities of M_i^v are denoted as $M_i^u = \{u_{ij} | j = 1, \ldots, k | k \le c\}$, where u_{ij} is the utility of its j_{th} solution, v_{ij}. For an agent, when the number of memorized solutions equals c, it must delete the oldest solution along with the corresponding utility from its memory if it wants to incorporate a new solution into its memory.

2.2.4. Agent Current Solution (State Variable).
Each agent has a current solution that is the solution in its memory with the highest utility.

2.2.5. Utility of Agent Current Solution (State Variable).
There is the utility of an agent's current solution.

2.2.6. Individual Utility Function (State Variable).
The individual utility function is completely based on the agent's memorized knowledge (i.e., those memorized solutions along with the utilities), which is typically biased because of limited information. Its definition is similar to the true utility function that is shown as follows:

$$U_i(v) = \frac{\sum_{j=1}^{k} u_{ij} D(v_{ij}, v)^{-2}}{\sum_{j=1}^{k} D(v_{ij}, v)^{-2}}, \quad (2)$$

where $v \notin M_i^v$ is a solution for the problem, u_{ij} is the utility value of the memorized solution $v_{ij} \in M_i^v$, and $D(v_{ij}, v)$ is the Euclidean distance between v_{ij} and v. When $v \in M_i^v$, $U_i(v) = u_{ij}$. To display an individual agent's bias in understanding a given problem space, Figure 1 gives a simple example of comparing a true utility function with a specific agent's individual utility function. The differences between them show this agent's cognitive or information limitation for comprehending this problem space. Moreover, each agent's individual utility function can be continuously updated through individual local search and incorporating others' proposals, which are described is Section 2.3.

2.2.7. Group Solution (State Variable).
At the group level, there is a tentative group solution (one point on the problem space) that is visible to every agent, which is assumed as none before the group discussion starts. At each time step, the group solution will be updated if there is one proposal approved by the group.

2.2.8. Utility of Group Solution (State Variable).
The utility of the group solution is obtained by the true utility function (i.e., formula (1)).

2.2.9. Ratio of Agreement (State Variable).
The ratio of agreement is a value obtained through the number of agents who support the speaker's proposal divided by the group size. It measures group consensus on a proposal in each group discussion round.

2.3. Process Overview and Scheduling.
Figure 2 gives the order of five the group phases in each discussion round, which includes individual local search, selection of a speaker, proposal of a new solution by the speaker, evaluation and response to the speaker's proposal by the listeners, and the overall response to the proposal at the group level. Figure 3 schematically shows an example of the process of independent searching and collaborative group searching on a given problem space. The detailed description of each group phase is as follows.
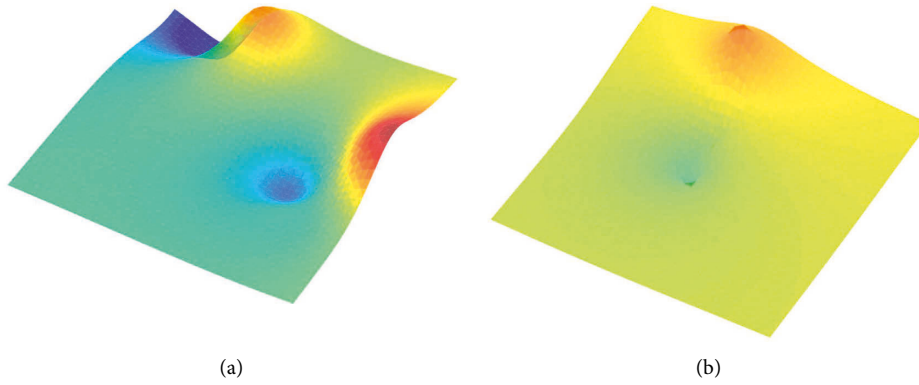
Figure 1: An example of a true utility function and a specific agent's individual utility function. (a) A given 2-dimension problem space (i.e., a true utility function). (b) An agent's individual representation of (a) (i.e., an individual utility function).
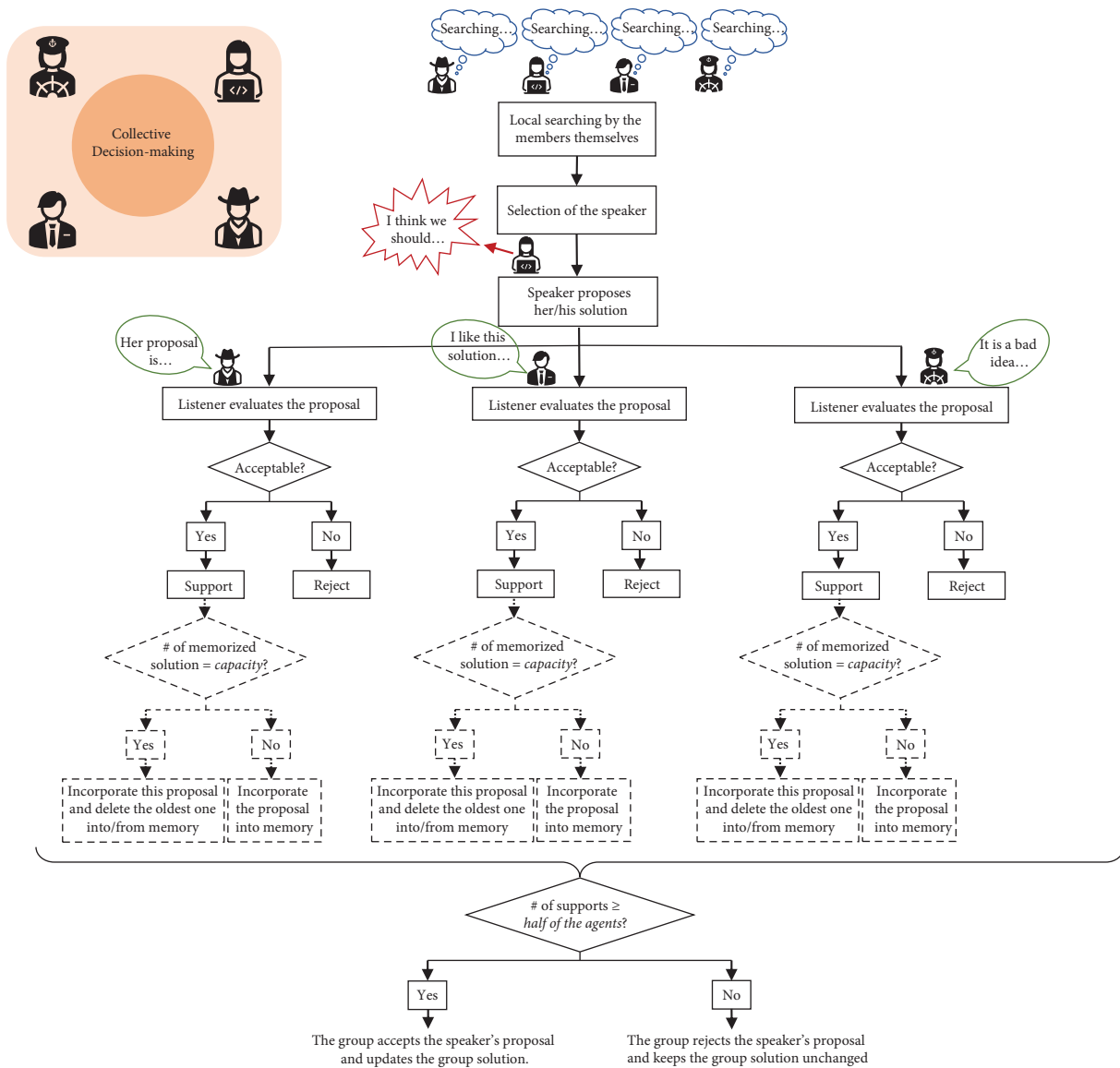

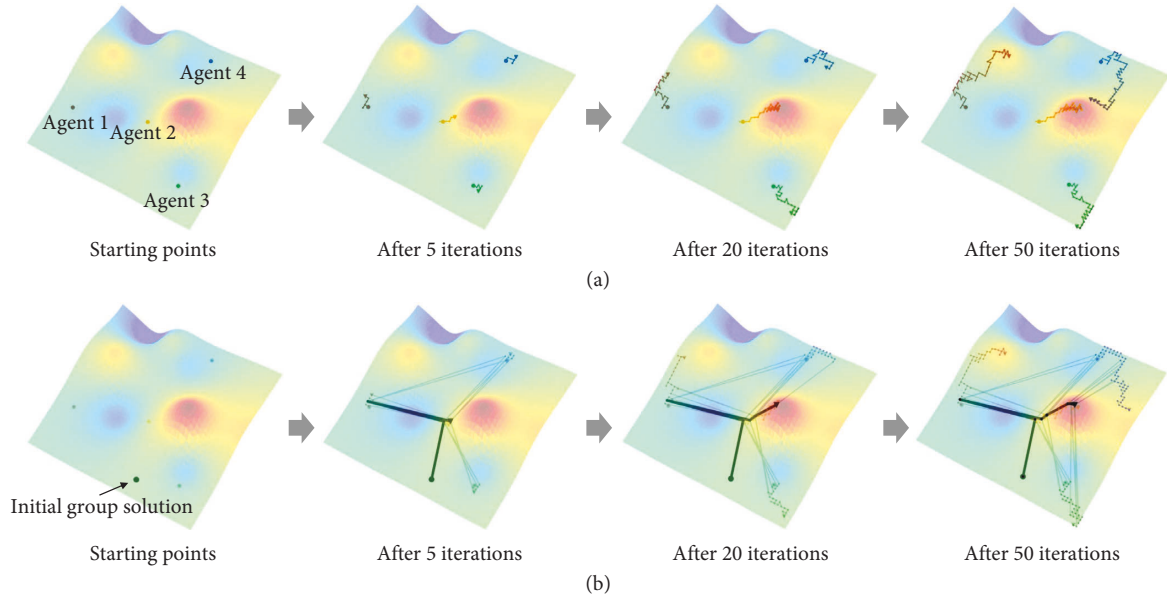
Figure 2: Overview of model process.

FIGURE 3: A schematic illustration of agents' searching process on a two-dimensional problem space. (a) Four agents independently search for the maximum solution using the "hill-climbing" strategy [70]. The starting and ending points are represented as a round dot and a triangle dot, respectively. The searching traces of agents 1, 2, 3, and 4 are displayed in thin brown, orange, green, and blue lines, respectively. (b) A group of four agents collaboratively search for the maximum solution using the "hill-climbing" strategy. The large round and triangle dots represent the starting and ending points of group searching. The group's searching trace is displayed in thicker black lines. *Note*. Each point in the problem space represents a solution, while the corresponding color denotes the value of the point. For example, dark red refers to a high value, whereas dark blue refers to a low value.

2.3.1. Local Search (Individual Agents). Each agent seeks to find better solutions by conducting a local search in the problem space at the beginning of each round of group discussion. This process is designed as a simple version of hill-climbing [68]. Each agent performs a way of "trial and error" in the process of local search, which can also be seen as learning through experimentation. In this model, each agent searches the neighbor solutions (e.g., four neighbor solutions in a two-dimensional problem space) of its current solution, randomly chooses one of the neighbor solutions as a candidate solution, and incorporates it into the memory for the next step. If the candidate solution is better than the agent's current solution, it updates its current solution by this candidate solution; otherwise, it keeps its current solution unchanged. If the quantity of the solutions in this agent's memory is reaching the memory capacity, c, then the oldest one is forgotten (i.e., removed from its memory). The individual local search process can be understood as a sequence of consideration of possible modifications of known solutions, which often leads to local peaks (i.e., suboptimal solutions). Note that we assume every agent's local search is noiseless in this work.

2.3.2. Selection of Speaker. The speaker in each group discussion is randomly selected with uniform probability from the entire group.

2.3.3. Proposal of a Solution by the Speaker. The speaker proposes its current solution and suggests replacing the group solution with its proposal.

2.3.4. Evaluation of Speaker's Proposal by Listeners. After the speaker proposes a solution, the other agents (listeners) evaluate the proposal and respond to it with either agreement (i.e., supporting) or disagreement (i.e., rejecting). If a listener agrees with the proposal, it incorporates the proposal and the corresponding utility (based on the listener's individual utility function) into its memory. If the number of solutions stored in the listener's memory exceeds the capacity c, then the oldest solution is removed from the listener's memory. Otherwise, it neglects this proposal and expresses disagreement.

A listener's evaluation of a proposal is based on a rational choice theory [71]. In this work, given a speaker s, it proposes a solution v_s. A listener l's evaluation of v_s is $U_l(v_s)$, which is calculated by its individual utility function. The listener l, according to the rationality setting, agrees with the proposal if $U_l(v_s)$ is higher than its current solution's utility. Meanwhile, we also assume that a listener may take a certain risk to accept those proposals that are inferior to its current solution because of either self-awareness of cognitive limitations [72, 73] or social effects [74, 75]. The risk level is represented as r_{th} in this model, which indicates the r_{th} percentile of the listener's best solutions (based on the utility) in memory. The listener disagrees with the proposal if $U_l(v_s)$ is lower than the utility of its r_{th} percentile of its best

solutions, $r_{\text{th}}(M_l^u)$. For a proposal whose utility is between the $r_{\text{th}}(M_l^u)$ and the utility of the listener's current solution, it stochastically agrees with the proposal according to a probability given in the following formula:

$$p = \frac{U_l(v_s) - r_{\text{th}}(M_l^u)}{\text{Max}(M_l^u) - r_{\text{th}}(M_l^u)}. \tag{3}$$

2.3.5. Response to Speaker's Proposal at Group Level. After all the listeners have made their agreement or disagreement decisions, the group as a whole responds to the speaker's proposal in a democratic manner. If more than half of the group members agree with the proposal, it will be accepted at the group level and the group solution will be replaced by this new solution proposed by the speaker. Otherwise, the group solution remains unchanged.

2.4. Design Concepts

2.4.1. Basic Principles. At the system level, this model addresses a management problem: what is the ideal group size for high group performance in various situations (time limitation, task complexity)? Such a question is especially interesting and complex when we understand group performance as an emergence from complex, dynamical interactions among group members rather than a simple summation or aggregation of properties of all group members in a group.

2.4.2. Emergence. The key outcome of this model is group performance (i.e., the utility of the group solution). It is dynamically driven by multiple factors in the group process including the agent's local search, the proposals by speakers, and the responses by the listeners. Moreover, group performance is also affected by group size and task complexity.

2.4.3. Adaptation. At the individual agent level, the adaptive behaviors of an agent are repositioning of their solutions on the problem space: the decision of which neighboring solutions move to (or remain where it was) or whether moving to the proposed solutions by speakers, considering the higher utilities of these alternatives. Moreover, each agent updates its memory and individual utility function by adding new solutions (local searching, shared solutions from others) in its memory or deleting old solutions from it. At the group level, the adaptive behavior of a group is updating the group solution on the problem space based on agents' proposals and the corresponding responses.

2.4.4. Learning. Each individual agent's learning process is defined as the local search, which means that each agent is directed at finding solutions that are superior to those currently known. Every agent explores one of its four adjacent neighboring (i.e., neighbor points located on the up, down, left, and right of the point) solutions at each time point and changes its solution to the one with higher utility

or remains where it was if the alternative is not better than its current solution.

2.4.5. Interaction. Interaction occurs through information sharing among the agents in a group, which includes speakers' proposing their new solutions and listeners' responses to (i.e., support, reject) the proposals.

2.4.6. Stochasticity. Stochasticity is used in five ways. First, each agent incorporates one solution at the beginning, which is randomly chosen on a problem space. Second, the speaker is randomly selected among the agents with a uniform probability (e.g., 1/4 for a group of four agents) in a group. Third, each agent randomly chooses one of its four neighboring alternative solutions to examine in the process of local search. Fourth, the listeners (i.e., the agents who are not the speaker at each time step) stochastically agree with the speaker's proposal according to a probability of p (see formula (3)). Finally, the problem space is also stochastically generated as the randomly given representative solutions. It may generate different true utility functions under the same parameter setting of the problem space.

2.4.7. Collectives. There is one collective in this model, a group of individual group members who share the same group goal and interact with each other in the problem-solving process.

2.4.8. Observation. The utility of group solution and the ratio of the agreement are the two major observations of this model. Additionally, the individual agent's current solution and memory are also observable but are not displayed in the simulation results.

2.5. Initialization. The related parameters are initialized as in Table 3. In this model, the problem space is a hypothetical model task or environment without agents' influence. Specifically, we defined three problem spaces with distinct complexity: 1-peak problem space (low complexity), 4-peak problem space (medium complexity), and 15-peak problem space (high complexity), as shown in Figure 4. These three problem spaces were selected as examples, in which the number of peaks was counted mathematically. We implemented these three typical problem spaces in all the computations. Each agent's initial solution was randomly selected (i.e., one point) from the given problem space, whereas the group solution is vacant at the beginning of the group discussion.

2.6. Input Data. Our agent-based model in this work does not include any input data describing the behaviors of agents, environmental conditions, or various tasks. Future model versions, however, might include data regarding agents' behaviors, such as participation rate, speaking turns, and social networks of mutual interactions among group members.

TABLE 3: Model parameter settings in the simulation experiments.

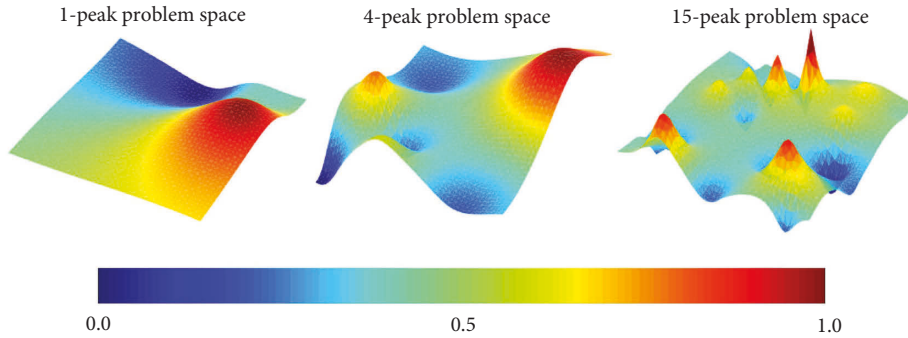| Parameter	Value	Description
m	2	Problem space dimensionality
n	50	Number of choices in each dimension
h	3, 7, 30	Number of representative solutions (for three problem spaces with distinct complexity)
q	5	A constant for generating a true utility function
c	20	Agent's memory capacity
r_{th}	50	r_{th} percentile of an agent's best solutions

FIGURE 4: Three typical two-dimension problem spaces of distinct complexity used in this work. Each point in the problem space represents a solution, while the corresponding color denotes the value of the point. For example, dark red refers to a high value, whereas dark blue refers to a low value. Those points on the corners or on the boundaries of the problem spaces can also be the peaks. Meanwhile, a few of the peaks may not be observable in this figure.

2.7. Submodels. There are two submodels in this work, the effective information sharing model and the ineffective information sharing model, which are used to study the effects of distinct ways of mutual information sharing on the relationship between group size and performance. Real-world information sharing among group members is related to many factors, such as trustworthiness [76], communication [77], cognitive ability [78], and leadership [79]. In our model, agents in groups practice information sharing through the speaker's proposing solutions and listeners' incorporating those solutions with which they agree. However, our previous definition of information sharing is superficial and ineffective because each listener's evaluation of the speaker's proposal is only based on its individual understanding of the problem space (see Section 2.3.4), which helps fill gaps of its coarse insights, yet it cannot reduce the understanding bias of the problem. We call this type of information sharing "ineffective information sharing."

On the contrary, we refer to "effective information sharing" as a process that can reshape the listener's mental model (individual utility function) and help bring the speaker's and listeners' understanding of the problem closer. To apply effective information sharing in our model, we modify two assumptions: the speaker's proposal and the listeners' evaluation of the proposal. Specifically, in each iteration, rather than proposing only a solution, a speaker needs to propose a solution and the corresponding utility simultaneously, say v_s and $U_s(v_s)$. Then, a listener, say l, whose current solution is v_l, evaluates this solution according to both its individual utility function, say $U_l(v_s)$ and the utility $U_s(v_s)$ provided by the speaker. The formula of listener l's evaluation is shown as follows.

$$U_l^e(v_s) = \left(1 - \frac{D(v_s, v_l)}{\sqrt[2]{m}}\right) \times U_s(v_s) + \frac{D(v_s, v_l)}{\sqrt[2]{m}} \times U_l(v_s),$$

(4)

where $(D(v_s, v_l)/\sqrt[2]{m})$ is the normalized distance between v_s and v_l, in which $D(v_s, v_l)$ and $\sqrt[2]{m}$ represent the Euclidean distance between v_s and v_l and the largest distance between any two points in a given m-dimensional problem space, respectively. The defined distance is used to measure the listener's comprehensibility of a proposed solution. According to this definition, the listener tends to consider its individual understanding $U_l(v_s)$ more when the speaker's proposal is closer to the listener's current solution (i.e., more comprehensible); otherwise (i.e., more incomprehensible), it tends to adopt the speaker's understanding $U_s(v_s)$ more. To some extent, it is an information integration process that will lead to a shared mental model in a group [80]. All other settings of this submodel of effective information sharing are the same as that of ineffective information sharing.

3. Results

We conducted simulation experiments on two-dimensional problem spaces at three distinct levels of complexity: 1-peak problem space (low complexity), 4-peak problem space (medium complexity), and 15-peak problem space (high complexity), which are described in Section 2.5 and shown in Figure 4. The group size was varied from 2 agents to 12 agents at intervals of 2 (6 different group sizes). Due to the stochastic nature of our model, we implemented Monte
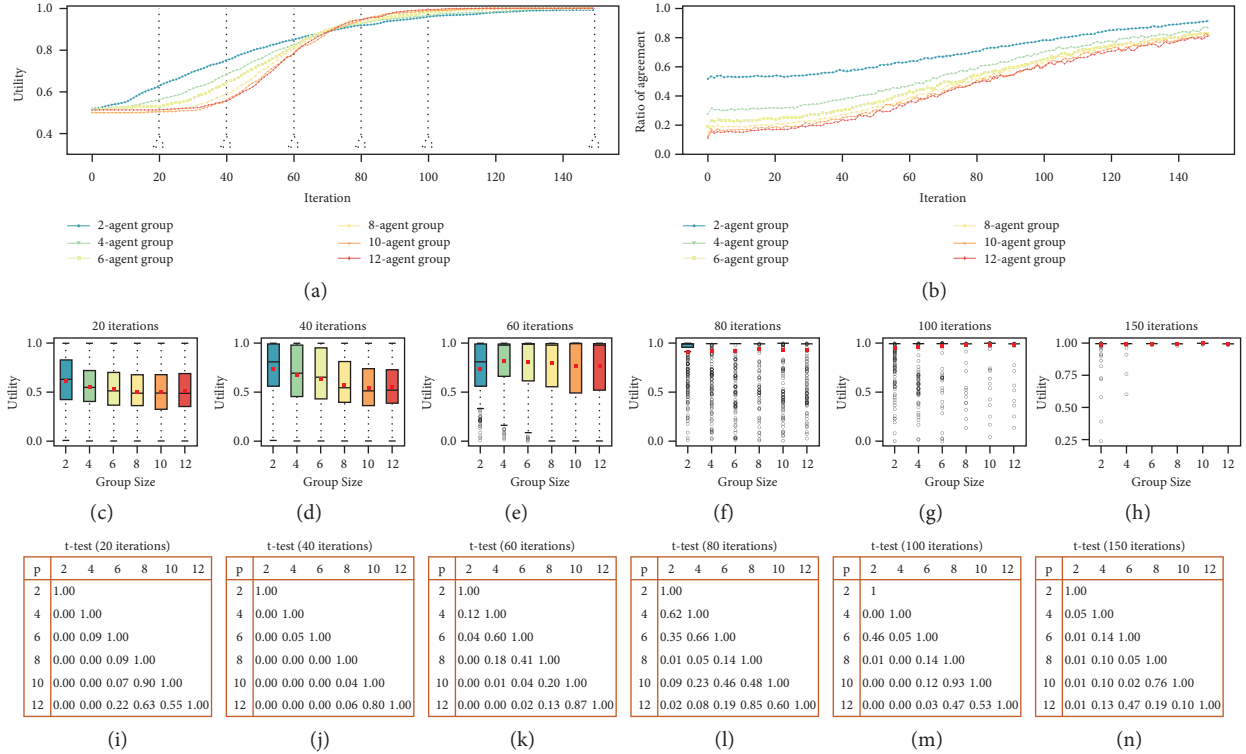
FIGURE 5: Change of utility of group solution (500 independent Monte Carlo experiments) and the ratio of agreement (500 independent Monte Carlo experiments) over iteration (discussion time) on 1-peak problem space. (a) Group performance over discussion time for groups of sizes 2, 4, 6, 8, 10, and 12. (b) Ratio of agreement over discussion time for groups of sizes 2, 4, 6, 8, 10, and 12. *Note.* Each curve shows the average result of 500 independent Monte Carlo experiments. (c) Utility of group solution after 20 iterations. (d) Utility of group solution after 40 iterations. (e) Utility of group solution after 60 iterations. (f) Utility of group solution after 80 iterations. (g) Utility of group solution after 100 iterations. (h) Utility of group solution after 150 iterations. Those boxplots in (c), (d), (e), (f), (g), and (h) represent the 25th and 75th percentiles of the group solution's utility of distinct group sizes across 500 independent Monte Carlo experiments. The black horizontal line and the red dot in each box indicate the median value and mean value, respectively. (i) t-test results of the utility of group solution among groups of distinct sizes after 20 iterations. (j) t-test results of the utility of group solution among groups of distinct sizes after 40 iterations. (k) t-test results of the utility of group solution among groups of distinct sizes after 60 iterations. (l) t-test results of the utility of group solution among groups of distinct sizes after 80 iterations. (m) t-test results of the utility of group solution among groups of distinct sizes after 100 iterations. (n) t-test results of the utility of group solution among groups of distinct sizes after 150 iterations.

Carlo simulations (500 independent replications) to obtain all the simulation results.

3.1. Task Complexity and Discussion Time.

Figures 5–7 give the changes of group solutions' utility (i.e., group performance) and the ratio of agreement over iteration (i.e., discussion time) under the condition of ineffective information sharing. As seen in Figure 5(a), the group performance increased monotonically over discussion time for all group sizes on the 1-peak problem space (i.e., the task of low complexity), which suggests all the groups were able to continually search for new solutions and improve the group performance. Figure 5(a) also shows smaller groups (e.g., 2-agent or 4-agent group) outperformed larger groups (e.g., 10-agent or 12-agent group) at the beginning of the discussion (e.g., before around 60 iterations), whereas they eventually (i.e., after 150 iterations) performed equally well in the long run in such a simple problem space. The group performances at distinct terms of the group discussion were also extracted and displayed in Figures 5(c)–5(h). To

demonstrate the statistical difference/similarity of these Monte Carlo simulation results, t-tests were implemented, which are shown in Figures 5(i)–5(n). These detailed results further bolster the trends in Figure 5(a). Though the 2-agent group's final solutions are significantly different from other groups (see the p value in Figure 5(n)), the averaged difference is still neglectable according to the results in Figure 5(a). As shown in Figure 5(b), all the ratios of agreements increased over discussion time. At the beginning of the discussion, smaller groups were more likely to reach agreements and tended to have more chances of exploring the problem space at the group level, which led to the phenomenon of smaller groups outperforming larger groups. Nevertheless, as the discussion progresses, larger groups were also able to achieve a high ratio of agreement that produced equally well solutions as smaller groups for the problem of low complexity.

Figure 6 gives the results for the 4-peak problem space (i.e., the task of medium complexity). As seen in Figures 6(a) and 6(c)–6(n), smaller groups still outperformed larger groups at the beginning of the group discussion (e.g., the first

(a)

(b)

(c)   (d)   (e)   (f)   (g)   (h)
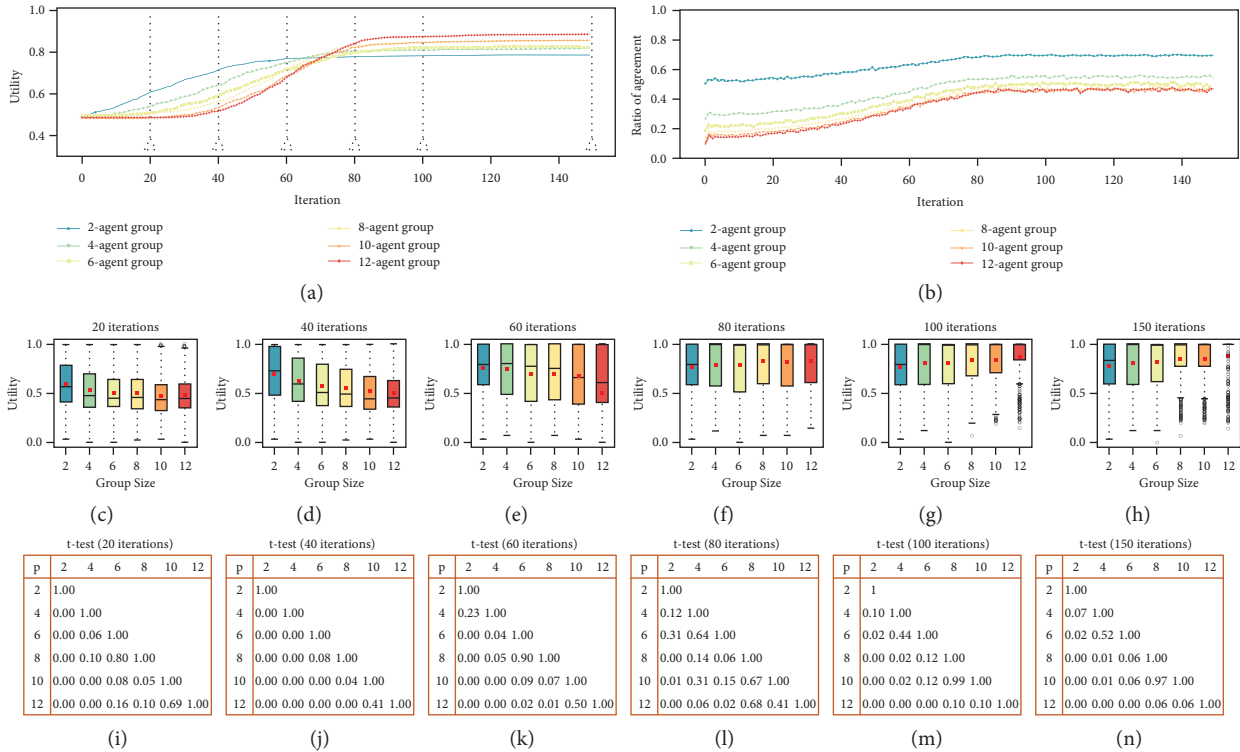
(i)   (j)   (k)   (l)   (m)   (n)

FIGURE 6: Change of utility of group solution (500 independent Monte Carlo experiments) and the ratio of agreement (500 independent Monte Carlo experiments) over iteration (discussion time) on 4-peak problem space.
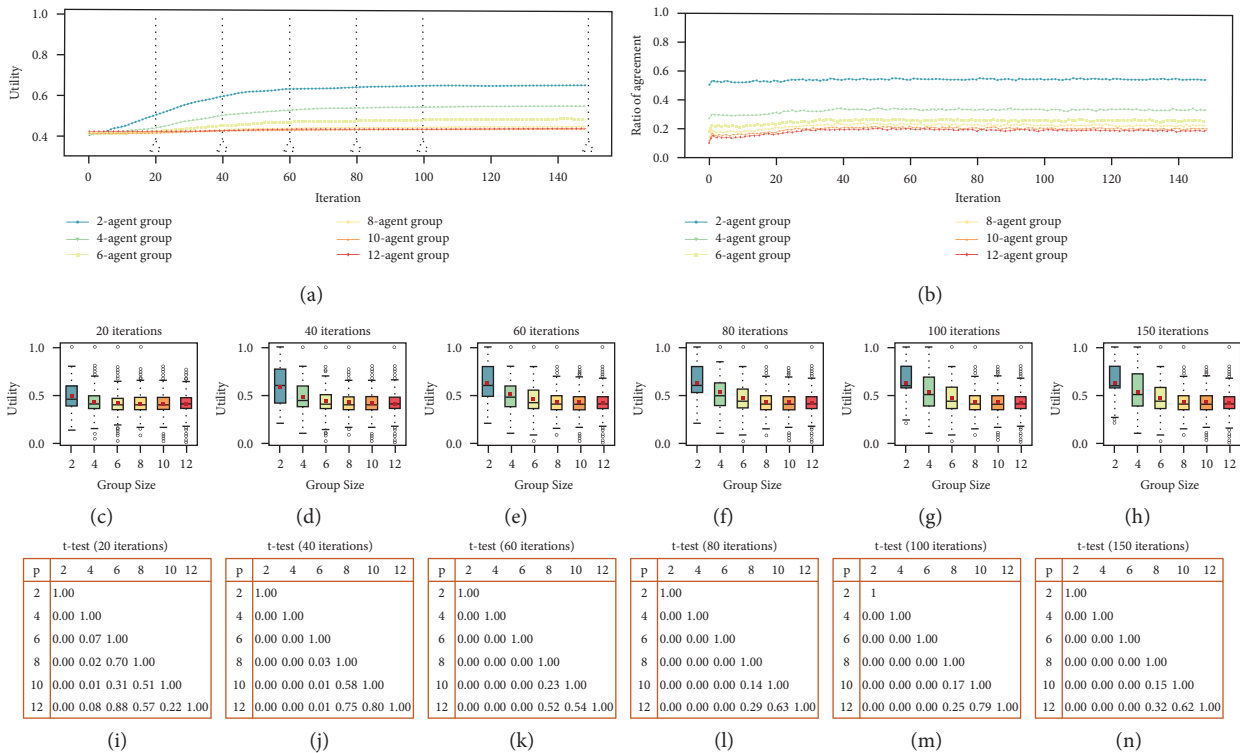

(a)

(b)

(c)   (d)   (e)   (f)   (g)   (h)

(i)   (j)   (k)   (l)   (m)   (n)

FIGURE 7: Change of utility of group solution (500 independent Monte Carlo experiments) and the ratio of agreement (500 independent Monte Carlo experiments) over iteration (discussion time) on 15-peak problem space.
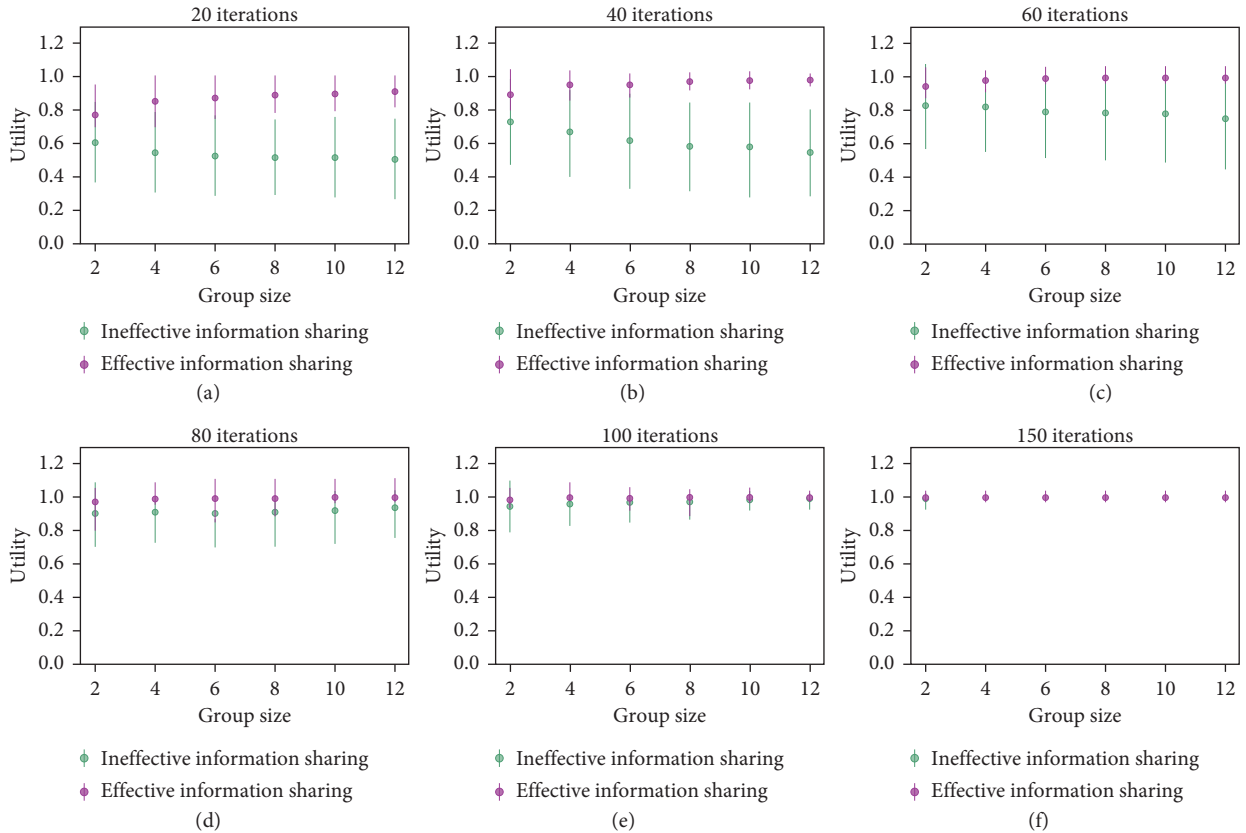
FIGURE 8: Bar plots regarding the effects of information sharing on group performance for the 1-peak problem space. Each dot represents the mean value, while each vertical line indicates the corresponding variance. (a) Group performance vs. group size for ineffective and effective sharing after 20 iterations. (b) Group performance vs. group size for ineffective and effective sharing after 40 iterations. (c) Group performance vs. group size for ineffective and effective sharing after 60 iterations. (d) Group performance vs. group size for ineffective and effective sharing after 80 iterations. (e) Group performance vs. group size for ineffective and effective sharing after 100 iterations. (f) Group performance vs. group size for ineffective and effective sharing after 150 iterations.

60 iterations) due to the higher ratio of agreement (see Figure 6(b)). However, the difference in solution utility among groups of different sizes tended to lessen and then eventually showed a reverse pattern after about the 70th iteration, where larger groups surpassed smaller groups in performance. This reverse pattern can be explained by the fact that smaller groups lack solution diversity and thus they are more likely to be stuck in suboptimal peaks, whereas larger groups with greater solution diversity can achieve better solutions as they are able to explore a broader range of the problem space. Recall that every agent's initial solution is randomly selected in the problem space. This means that larger groups have more starting points and are more inclined to explore a larger range in the problem space. At the same time, larger groups can also reach fewer, but sufficient, agreements, as seen in Figure 6(b).

Figure 7 provides the results for the 15-peak problem space (i.e., the task of high complexity). As seen in Figures 7(a) and 7(c)–7(n), smaller groups outperformed larger groups throughout most of the group discussion time, as smaller groups were able to reach relatively higher ratios of agreement and had more chances to explore the problem space at the group level. Meanwhile, the greater diversity of solutions in larger groups hindered the groups' ability to

reach consensus (Figure 7(b)), which led to very few chances to explore the problem space.

Therefore, larger groups' performances were very low, some of which (e.g., 10-agent and 12-agent groups) were not improved at all during the whole collaborative decision-making process. Additionally, by comparing the results in Figures 5–7, we can also observe that both group performance and the ratio of agreement generally decreased as the complexity of the problem space increased.

3.2. Effective and Ineffective Information Sharing.
Finally, we applied effective information sharing to the model to study the impacts of the ways of information sharing in collaborative decision-making. Figures 8–10 show the results by comparing the ineffective and effective information sharing for different sized groups on the problem spaces of distinct complexity.

As seen in Figures 8–10, all groups practicing effective information sharing outperformed the groups of corresponding sizes by performing ineffective information sharing. Moreover, larger groups can achieve better (at least equal good) solutions than smaller groups over the whole group discussion process for all three tasks of distinct
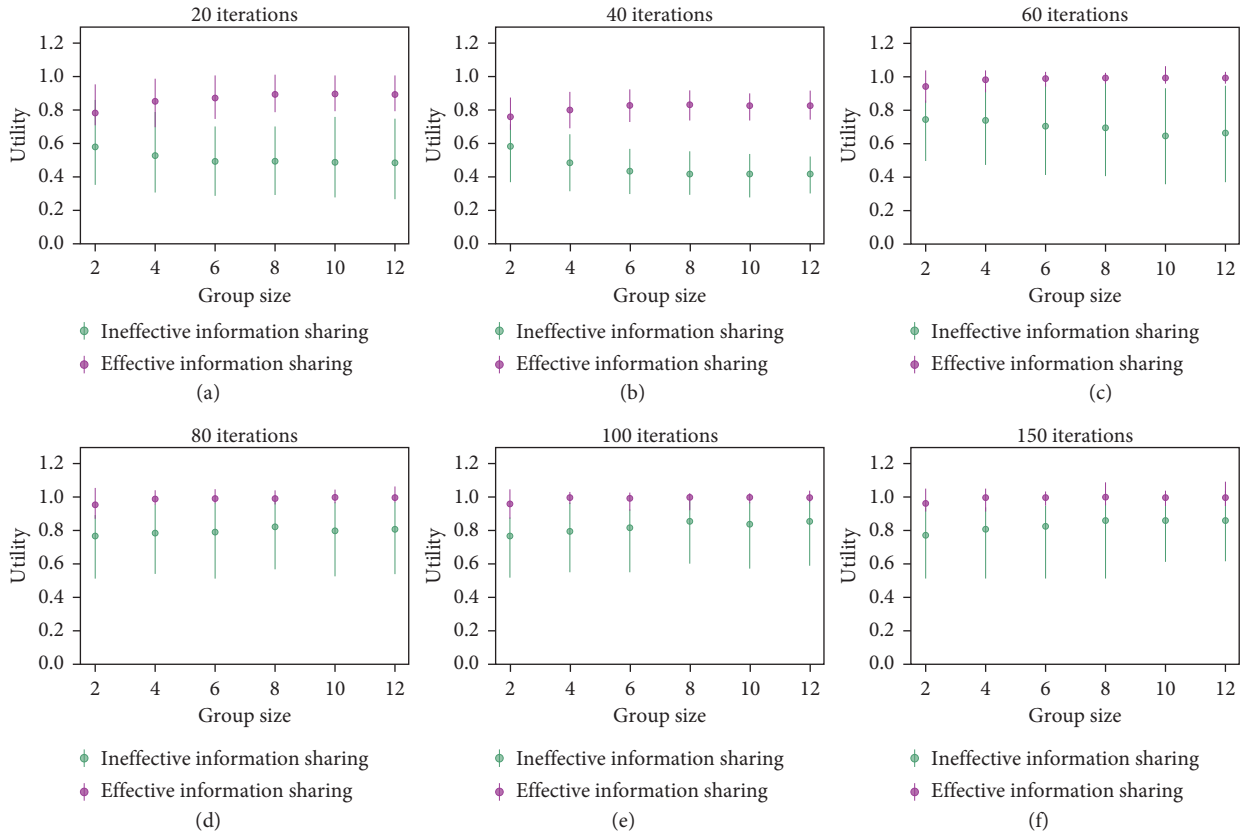
FIGURE 9: Bar plots regarding the effects of information sharing on group performance for the 4-peak problem space.

complexity. This suggests effective information sharing especially benefits larger groups, which is particularly visible at the beginning of the group discussion (Figures 8(a), 9(a), and 10(a)(a)), and for the task of high complexity both at the beginning and at the end of the discussion (Figure 10). The effective information sharing condition appears to operate by weakening or eliminating the negative side effects of the solution diversity in larger groups [76, 77].

3.3. Steady State.
The steady state of our model depends on the utility of the group solution (i.e., group performance) as it is the major output of our model. Here, the steady state does not mean that all the utilities of group solutions will all take on the same value in a particular simulation run; rather, it means that they will all have approximately the same distribution [81]. According to the simulation results in Figures 5(a), 6(a), and 7(a), the performance of each group of distinct size achieves a steady state after about 150 iterations for the task of low complexity, 85 iterations for the task of medium complexity, and 100 iterations for the task of high complexity, respectively. For comparison reasons, we stopped running our model after 150 iterations, when the utility of the group solution entered a steady state for all the studied groups in various situations.

3.4. Sensitivity Analysis.
Our model outputs were most sensitive to agent memory capacity c and the percentile of an agent's best solutions r_{th} in a listener's evaluation of a proposal (see Section 2.3.4). We tested minor variations of these two parameters and confirmed that the main results and conclusions were not significantly changed. For example, when we varied 25% of c or 20% of r_{th}, the simulation results regarding the relationship between group size and performance kept unchanged.

4. Discussion

In this study, we developed an agent-based model and examined the relationship between size and performance of collaborative small human groups. Our simulation results revealed that when the complexity of the problem was low and information sharing was limited, smaller groups outperformed larger groups at the beginning of the collective decision-making process, but all the groups performed equally well in the long run. With increased problem complexity, however, finding global optimum solutions became more difficult as groups need more diverse candidate solutions to achieve a better group-level solution. Thus, although smaller groups outperformed larger groups initially, larger groups ultimately found better solutions because of their higher solution diversity. When the problem complexity is very high, larger groups suffered from frequent within-group disagreements, which lead to lower group performance. Meanwhile, our results also suggested that enhancing the effectiveness of information sharing (by making participants pay more
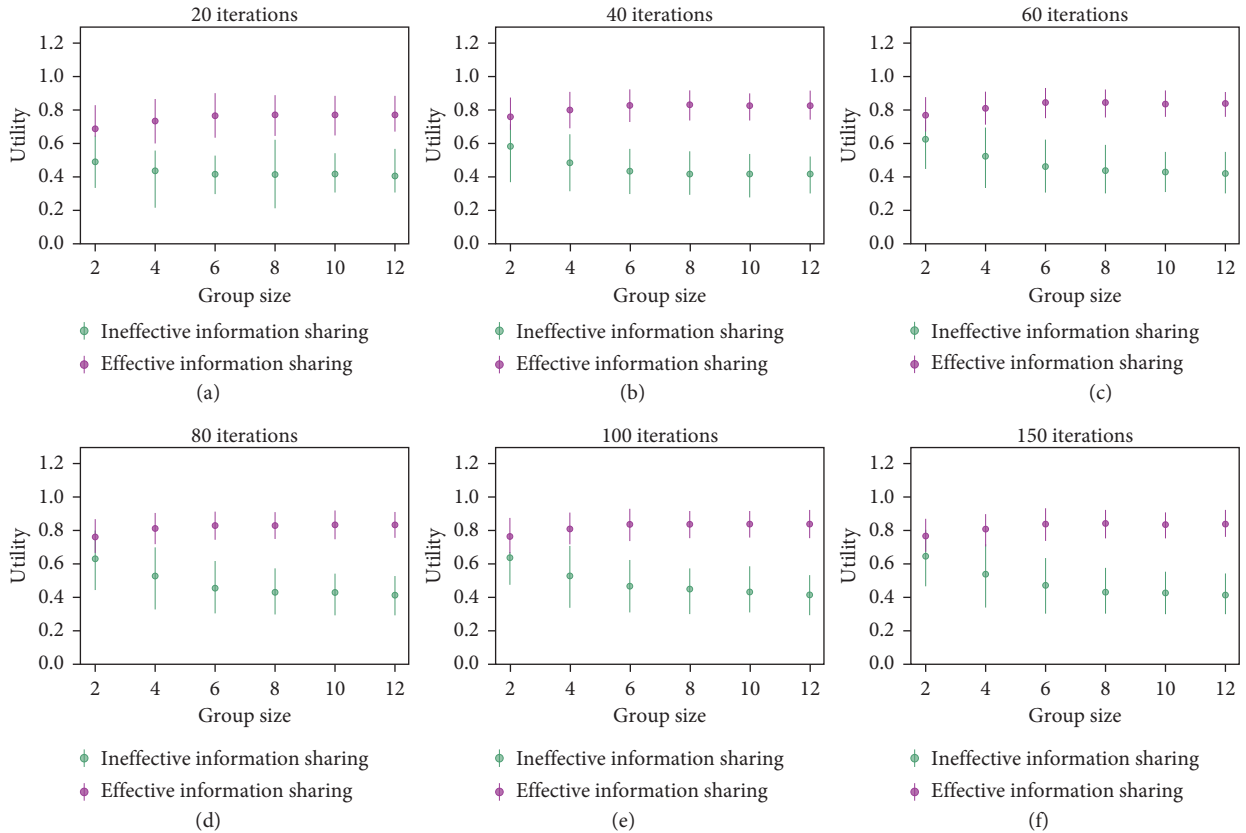
FIGURE 10: Bar plots regarding the effects of information sharing on group performance for the 15-peak problem space.

respect to others' opinions in the problem areas in which they are not so familiar) could improve group performance for groups of any size in the context of small collaborative team settings. This effect was most significant for larger groups. It also helped achieve a consistent, monotonic relationship between group size and group performance in all conditions. These findings collectively paint a whole picture of various nontrivial relationships between group size and group performance, in which most of the previously reported empirical findings can be mapped. Therefore, our model helps bridge the gap among the conflicting observations on this topic from a mechanistic modeling viewpoint. Our model also provides a baseline for further theoretical and experimental studies concerning group size and group performance in small human groups. It allows researchers to explore trade-offs when adding other factors into this model, such as roles, learning methods, ways of mutual interactions, and dynamics of tasks.

Our study has several practical implications. First, our findings underscore the importance of the amount of given time and task complexity in group size selection for real-world collaborative group building. For example, if a rapid and tolerable decision is expected, a smaller team is often a good choice; whereas if an optimum group decision is expected for completing relatively simple or medium complex tasks and will provide enough time for group discussion, a larger group will be superior to smaller groups. Second,

highly complex tasks often require more diverse expertise and perspectives, yet using a large group to solve problems of high complexity may lead to less than optimum group decisions. Third, our model suggested specific features of information sharing that may improve group performance, particularly in larger groups, such as fostering mutual learning across expertise areas through coordinated communication. A real-world example could be a business company trying to form a committee to handle an emergent risk regarding supply chains. Potential committee members could be specialists or managers with distinct perspectives (e.g., marketing, research and development, production, finance). The issue for the company is what the best committee size will be to minimize the cost of the supply chain problem immediately. Our work then can serve as a valuable reference for building an effective committee of appropriate size.

Besides, our model also has several limitations. First, the validation of our simulation results is missing in our work. Though the reported empirical observations, in turn, can serve as partial validation for the results in distinct situations, systematic human-subject experimental studies are still needed to validate this work. In the future, we plan to organize a series of human-subject experiments to justify our simulations, which will include participants with diverse perspectives and backgrounds, tasks with tunable complexity, measurements of group performance over the group discussion time, etc. Second, the agent's roles (e.g., leader,

meditator) and abilities (e.g., intelligence, expertise) were not considered, which may affect the selection of speaker, the accuracy of individual local search, and the mutual interactions among group members, etc. Those members with high social status or leadership may also help a group reach agreement and thus reduce the negative effects of high solution diversity. Therefore, a promising direction for future research is to incorporate more relevant properties of the agents to extend this model's application scenarios. Third, information sharing within a group may also depend on members' roles, personalities, and backgrounds, as well as on communication platforms or environments. Studying the impact of various information-sharing strategies in both computational and experimental means can deepen our understanding of collaborative decision-making. Fourth, the assumption of the agent's incrementally "hill-climbing" searching method may be too stringent as the creative searching may also enable agents to broaden the search in each iteration (comparing with searching neighbors) through randomly changing more values in its current solution or integrating distinct solutions (e.g., individual's current solution and a proposed solution by a speaker). This type of search process includes "long jump" [68], "radical innovation" [82], and "Lévy flight" [83], which may produce different simulation results. In the future, we plan to adopt and compare distinct search strategies in this model to examine how they impact the relationship between group size and performance. Fifth, we assumed that every group member's local search and evaluation of others' proposals are errorless, which is difficult to achieve in the real world. Sixth, our definition of task complexity was also limited as it is mainly based on the rugged level of the two-dimension problem spaces. We plan to investigate the dimension complexity of problem space and study the sensibility of group performance over dimensions in our future modeling work. Finally, we plan to conduct more systematic model calibration and fitting so that this model will be more valuable in predicting and guiding practical collaborative decision-making.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

References

[1] S. R. Sommers, "On racial diversity and group decision making: identifying multiple effects of racial composition on jury deliberations," *Journal of Personality and Social Psychology*, vol. 90, no. 4, pp. 597–612, 2006.

[2] R. J. MacCoun, "Experimental research on jury decision-making," *Science*, vol. 244, no. 4908, pp. 1046–1050, 1989.

[3] E. H. Allern and T. Bale, "Political parties and interest groups," *Party Politics*, vol. 18, no. 1, pp. 7–25, 2012.

[4] J. Baker, J. Cote, and B. Abernethy, "Sport-specific practice and the development of expert decision-making in team ball sports," *Journal of Applied Sport Psychology*, vol. 15, no. 1, pp. 12–25, 2003.

[5] B. A. Nijstad and C. K. W. De Dreu, "Creativity and group innovation," *Applied Psychology*, vol. 51, no. 3, pp. 400–406, 2002.

[6] R. L. Moreland, J. M. Levine, and M. L. Wingert, "Creating the ideal group: composition effects at work," in *Understanding Group Behavior*, pp. 11–35, Psychology Press, London, England, UK, 2018.

[7] M. Higgs, U. Plewnia, and J. Ploch, "Influence of team composition and task complexity on team performance," *Team Performance Management: International Journal*, vol. 11, no. 7/8, pp. 227–250, 2005.

[8] S. T. Bell, "Deep-level composition variables as predictors of team performance: a meta-analysis," *Journal of Applied Psychology*, vol. 92, no. 3, pp. 595–615, 2007.

[9] L. Argote and J. E. McGrath, "Group processes in organizations: continuity and change," *International Review of Industrial and Organizational Psychology*, vol. 8, pp. 333–389, 1993.

[10] D. van Knippenberg, C. K. W. De DreuDe Dreu, and A. C. Homan, "Work group diversity and group performance: an integrative model and research agenda," *Journal of Applied Psychology*, vol. 89, no. 6, pp. 1008–1022, 2004.

[11] J. A. Chatman, L. L. Greer, E. Sherman, and B. Doerr, "Blurred lines: how the collectivism norm operates through perceived group diversity to boost or harm group performance in Himalayan mountain climbing," *Organization Science*, vol. 30, no. 2, pp. 235–259, 2019.

[12] W. G. Graziano, E. C. Hair, and J. F. Finch, "Competitiveness mediates the link between personality and group performance," *Journal of Personality and Social Psychology*, vol. 73, no. 6, pp. 1394–1408, 1997.

[13] A. Kramer, D. P. Bhave, and T. D. Johnson, "Personality and group performance: the importance of personality composition and work tasks," *Personality and Individual Differences*, vol. 58, pp. 132–137, 2014.

[14] T. Halfhill, T. M. Nielsen, E. Sundstrom, and A. Weilbaecher, "Group personality composition and performance in military service teams," *Military Psychology*, vol. 17, no. 1, pp. 41–54, 2005.

[15] G. Littlepage, W. Robison, and K. Reddington, "Effects of task experience and group experience on group performance, member ability, and recognition of expertise," *Organizational Behavior and Human Decision Processes*, vol. 69, no. 2, pp. 133–147, 1997.

[16] M. Goldman, "A comparison of individual and group performance for varying combinations of initial ability," *Journal of Personality and Social Psychology*, vol. 1, no. 3, pp. 210–216, 1965.

[17] N. Ellemers, D. De Gilder, and S. A. Haslam, "Motivating individuals and groups at work: a social identity perspective

on leadership and group performance," *Academy of Management Review*, vol. 29, no. 3, pp. 459–478, 2004.

[18] M. L. Newman, J. G. Sellers, and R. A. Josephs, "Testosterone, cognition, and social status," *Hormones and Behavior*, vol. 47, no. 2, pp. 205–211, 2005.

[19] S. G. Harkins and K. Szymanski, "Social loafing and group evaluation," *Journal of Personality and Social Psychology*, vol. 56, no. 6, pp. 934–941, 1989.

[20] B. Holmstrom, "Moral hazard in teams," *The Bell Journal of Economics*, vol. 13, no. 2, pp. 324–340, 1982.

[21] S. J. Karau and K. D. Williams, "Social loafing: a meta-analytic review and theoretical integration," *Journal of Personality and Social Psychology*, vol. 65, no. 4, pp. 681–706, 1993.

[22] A. G. Ingham, G. Levinger, J. Graves, and V. Peckham, "The Ringelmann effect: studies of group size and group performance," *Journal of Experimental Social Psychology*, vol. 10, no. 4, pp. 371–384, 1974.

[23] P. B. Lowry, T. L. Roberts, N. C. Romano, P. D. Cheney, and R. T. Hightower, "The impact of group size and social presence on small-group communication," *Small Group Research*, vol. 37, no. 6, pp. 631–661, 2006.

[24] J. Lorenz, H. Rauhut, F. Schweitzer, and D. Helbing, "How social influence can undermine the wisdom of crowd effect," *in Proceedings of the National Academy of Sciences*, vol. 108, no. 22, pp. 9020–9025, 2011.

[25] B. Latané, K. Williams, and S. Harkins, "Many hands make light the work: the causes and consequences of social loafing," *Journal of Personality and Social Psychology*, vol. 37, no. 6, pp. 822–832, 1979.

[26] R. A. Weber, "Managing growth to achieve efficient coordination in large groups," *The American Economic Review*, vol. 96, no. 1, pp. 114–126, 2006.

[27] G. M. Wittenbaum, S. I. Vaughan, and G. Strasser, "Coordination in task-performing groups," in *Theory and Research on Small Groups*, pp. 177–204, Springer, Boston, MA, 2002.

[28] A. Mao, W. Mason, S. Suri, and D. J. Watts, "An experimental study of team size and performance on a complex task," *PLoS One*, vol. 11, no. 4, p. e0153048, 2016.

[29] M. A. Campion, G. J. Medsker, and A. C. Higgs, "Relations between work group characteristics and effectiveness: implications for designing effective work groups," *Personnel Psychology*, vol. 46, no. 4, pp. 823–847, 1993.

[30] M. Argyle, G. Gardner, and F. Cioffi, "Supervisory methods related to productivity, absenteeism, and labour turnover," *Human Relations*, vol. 11, no. 1, pp. 23–40, 1958.

[31] R. A. Guzzo and G. P. Shea, "Group performance and intergroup relations in organizations," in *Handbook of Industrial and Organizational Psychology*, M. D. Dunnette and L. M. Hough, Eds., pp. 269–313, Consulting Psychologists Press, Palo Alto, CA, USA, 1992.

[32] J. R. Hackman, *Groups that Work and Those that Don't (No. E10 H123)*, Jossey-Bass, San Francisco, CA, USA, 1990.

[33] V. F. Nieva, E. A. Fleishman, and A. Rieck, *Team Dimensions: Their Identity, Their Measurement and Their Relationships*, Advanced Research Resources Organization, Bethesda Md USA, 1985.

[34] T. J. Bouchard, J. Barsaloux, and G. Drauden, "Brainstorming procedure, group size, and sex as determinants of the problem-solving effectiveness of groups and individuals," *Journal of Applied Psychology*, vol. 59, no. 2, pp. 135–138, 1974.

[35] W. B. Martz, D. R. Vogel, and J. F. Nunamaker, "Electronic meeting systems," *Decision Support Systems*, vol. 8, no. 2, pp. 141–158, 1992.

[36] R. M. Bray, N. L. Kerr, and R. S. Atkin, "Effects of group size, problem difficulty, and sex on group performance and member reactions," *Journal of Personality and Social Psychology*, vol. 36, no. 11, pp. 1224–1240, 1978.

[37] L. R. Weingart, "Impact of group goals, task component complexity, effort, and planning on group performance," *Journal of Applied Psychology*, vol. 77, no. 5, pp. 682–693, 1992.

[38] L. Argote, C. A. Insko, N. Yovetich, and A. A. Romero, "Group learning curves: the effects of turnover and task complexity on group Performance1," *Journal of Applied Social Psychology*, vol. 25, no. 6, pp. 512–529, 1995.

[39] B. B. Morgan, E. Salas, and A. S. Glickman, "An analysis of team evolution and maturation," *The Journal of General Psychology*, vol. 120, no. 3, pp. 277–291, 1993.

[40] M. J. Pearsall, A. P. J. EllisEllis, and B. S. Bell, "Building the infrastructure: the effects of role identification behaviors on team cognition development and performance," *Journal of Applied Psychology*, vol. 95, no. 1, pp. 192–200, 2010.

[41] M. A. Marks, J. E. Mathieu, and S. J. Zaccaro, "A temporally based framework and taxonomy of team processes," *Academy of Management Review*, vol. 26, no. 3, pp. 356–376, 2001.

[42] S. Milojević, "Principles of scientific research team formation and evolution," in *Proceedings of the National Academy of Sciences*, vol. 111, no. 11, pp. 3984–3989, 2014.

[43] K. M. Nelson and J. G. Cooprider, "The contribution of shared knowledge to IS group performance," *MIS Quarterly*, vol. 20, no. 4, pp. 409–432, 1996.

[44] N. A. Moye and C. W. Langfred, "Information sharing and group conflict: going beyond decision making to understand the effects of information sharing on group performance," *International Journal of Conflict Management*, vol. 15, no. 4, pp. 381–410, 2004.

[45] C. M. Macal and M. J. North, "Agent-based modeling and simulation," in *Proceedings of the 2009 Winter Simulation Conference (WSC)*, pp. 86–98, IEEE, Austin, TX USA, 2009, December.

[46] H. Sayama, D. L. Farrell, and S. D. Dionne, "The effects of mental model formation on group decision making: an agent-based simulation," *Complexity*, vol. 16, no. 3, pp. 49–57, 2011.

[47] J. Langevin, J. Wen, and P. L. Gurian, "Simulating the human-building interaction: development and validation of an agent-based model of office occupant behaviors," *Building and Environment*, vol. 88, pp. 27–45, 2015.

[48] A. Lungeanu, S. Sullivan, U. Wilensky, and N. S. Contractor, "A computational model of team assembly in emerging scientific fields," in *Proceedings of the 2015 Winter Simulation Conference (WSC)*, pp. 4057–4068, IEEE, Huntington Beach, CA, 2015, December.

[49] D. L. Gladstein, "Groups in context: a model of task group effectiveness," *Administrative Science Quarterly*, vol. 29, no. 4, pp. 499–517, 1984.

[50] S. G. Cohen, G. E. Ledford, and G. M. Spreitzer, "A predictive model of self-managing work team effectiveness," *Human Relations*, vol. 49, no. 5, pp. 643–676, 1996.

[51] S. M. Reia, A. C. Amado, and J. F. Fontanari, "Agent-based models of collective intelligence," *Physics of Life Reviews*, vol. 31, pp. 320–331, 2019.

[52] H. Sayama and S. D. Dionne, "Studying collective human decision making and creativity with evolutionary computation," *Artificial Life*, vol. 21, no. 3, pp. 379–393, 2015.

[53] S. Lapp, K. Jablokow, and C. McComb, "KABOOM: an agent-based model for simulating cognitive style in team problem solving," *Design Science*, vol. 5, p. e13, 2019.

[54] R. P. Mann, "Collective decision making by rational individuals," *in Proceedings of the National Academy of Sciences*, vol. 115, no. 44, pp. E10387–E10396, 2018.

[55] L. Conradt, "Models in animal collective decision-making: information uncertainty and conflicting preferences," *Interface focus*, vol. 2, no. 2, pp. 226–240, 2012.

[56] S. D. Dionne, H. Sayama, C. Hao, and B. J. Bush, "The role of leadership in shared mental model convergence and team performance improvement: an agent-based computational model," *The Leadership Quarterly*, vol. 21, no. 6, pp. 1035–1049, 2010.

[57] S. Cao, N. G. MacLaren, Y. Cao et al., "An Agent-Based Model of Leader Emergence and Leadership Perception within a Collective," *Complexity*, vol. 2020, Article ID 6857891, 11 pages, 2020.

[58] T. Bosse, R. Duell, Z. A. Memon, J. Treur, and C. N. van der Wal, "Computational model-based design of leadership support based on situational leadership theory," *SIMULATION*, vol. 93, no. 7, pp. 605–617, 2017.

[59] S. F. Railsback and V. Grimm, *Agent-based and Individual-Based Modeling: A Practical Introduction*, Princeton university press, Princeton, NJ USA, 2019.

[60] N. Becu, A. Neef, P. Schreinemachers, and C. Sangkapitux, "Participatory computer simulation to support collective decision-making: potential and limits of stakeholder involvement," *Land Use Policy*, vol. 25, no. 4, pp. 498–509, 2008.

[61] H. Rahmandad and J. Sterman, "Heterogeneity and network structure in the dynamics of diffusion: comparing agent-based and differential equation models," *Management Science*, vol. 54, no. 5, pp. 998–1014, 2008.

[62] E. Bonabeau, "Agent-based modeling: methods and techniques for simulating human systems," *in Proceedings of the National Academy of Sciences*, vol. 99, no. suppl3, pp. 7280–7287, 2002.

[63] H. A. Simon, "A behavioral model of rational choice," *Quarterly Journal of Economics*, vol. 69, no. 1, pp. 99–118, 1955.

[64] J. G. March and H. A. Simon, *Organizations*, John Wiley & Sons, Hoboken, NJ, USA, 1993.

[65] R. Likert, J. L. Gray, and F. A. Starke, Eds., *Readings in Organizational Behavior*, Merrill, Columbus, OH USA.

[66] J. Henrich, "Cultural group selection, coevolutionary processes and large-scale cooperation," *Journal of Economic Behavior & Organization*, vol. 53, no. 1, pp. 3–35, 2004.

[67] V. Grimm, S. F. Railsback, C. E. Vincenot et al., "The ODD protocol for describing agent-based and other simulation models: a second update to improve clarity, replication, and structural realism," *The Journal of Artificial Societies and Social Simulation*, vol. 23, no. 2, 2020.

[68] D. A. Levinthal, "Adaptation on rugged landscapes," *Management Science*, vol. 43, no. 7, pp. 934–950, 1997.

[69] O. Baumann, J. Schmidt, and N. Stieglitz, "Effective search in rugged performance landscapes: a review and outlook," *Journal of Management*, vol. 45, no. 1, pp. 285–318, 2019.

[70] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, Pearson, London, England, 2002.

[71] J. Scott, "Rational choice theory," *Understanding contemporary society: Theories of the present*, vol. 129, pp. 671–685, 2000.

[72] R. Hertwig and P. M. Todd, "More is not always better: the benefits of cognitive limits," *Thinking: Psychological Perspectives on Reasoning, Judgment and Decision Making*, pp. 213–231, Wiley, Hoboken, New Jersey USA, 2003.

[73] M. P. Keane and S. Thorp, "Complex decision making," *Handbook of the economics of population aging*, vol. 1pp. 661–709, North-Holland, 2016.

[74] D. Tjosvold and R. H. G. Field, "Effects of social context on consensus and majority vote decision making," *Academy of Management Journal*, vol. 26, no. 3, pp. 500–506, 1983.

[75] P. Liu, R. Yang, and Z. Xu, "Public acceptance of fully automated driving: effects of social trust and risk/benefit perceptions," *Risk Analysis*, vol. 39, no. 2, pp. 326–341, 2019.

[76] J. H. Dyer and W. Chu, "The role of trustworthiness in reducing transaction costs and improving performance: empirical evidence from the United States, Japan, and Korea," *Organization Science*, vol. 14, no. 1, pp. 57–68, 2003.

[77] M. Gumus, "The effect of communication on knowledge sharing in organizations," *Journal of Knowledge Management Practice*, vol. 8, no. 2, pp. 15–26, 2007.

[78] P. J. Hinds and J. Pfeffer, "Why Organizations Don't "Know what They Know": Cognitive And Motivational Factors Affecting the Transfer of Expertise," *Sharing Expertise: beyond Knowledge Management*, pp. 3–26, MIT Press, Cambridge, MA USA, 2003.

[79] C. K. Lam, X. Huang, and S. C. H. ChanChan, "The threshold effect of participative leadership and the role of leader information sharing," *Academy of Management Journal*, vol. 58, no. 3, pp. 836–855, 2015.

[80] P. Van den Bossche, W. Gijselaers, M. Segers, G. Woltjer, and P. Kirschner, "Team learning: building shared mental models," *Instructional Science*, vol. 39, no. 3, pp. 283–301, 2011.

[81] A. M. Law, *Simulation Modeling and Analysis*, McGraw-Hill, New York, 2015.

[82] R. O. Chao and S. Kavadias, "A theoretical framework for managing the new product development portfolio: when and how to use strategic buckets," *Management Science*, vol. 54, no. 5, pp. 907–921, 2008.

[83] A. Baronchelli and F. Radicchi, "Lévy flights in human behavior and cognition," *Chaos, Solitons & Fractals*, vol. 56, pp. 101–105, 2013.