

Contents lists available at ScienceDirect

Journal of Engineering and Technology Management

journal homepage: www.elsevier.com/locate/jengtecman



Mutual perturbations in coupled exploration: Diverse impacts of feedback frequency and feedback timing



Jie Mi a,*,1, Jiamin Dong b

- ^a School of Economics and Management, Taiyuan University of Technology, China
- ^b Business School, Central South University, China

ARTICLE INFO

Keywords:
Coupled exploration
Perturbation
Feedback mechanism
Computational experiments
Multi-agent simulation

ABSTRACT

In the process of coupled exploration, when feedback from other teams comes in the form of disapproval, comments, and suggestions, teams may need to modify the existing technical routes or even abandon previous choices, which can perturb their ongoing exploration activities. We employ a multi-agent computational model to analyze the aforementioned processes. We have found that frequent perturbations among the R&D teams responsible for various subsystems can significantly impact the performance of coupled exploration, which is highly dependent on the speed at which teams search for better options and reach consensus. During the initial phase of coupling exploration, frequent perturbations permanently alter the trajectory of the exploration process. The reciprocal perturbation during the intermediate stage enhances the capacity for coupled exploration in subsequent stages, contingent upon the actor's adeptness in swiftly discerning and selecting optimal strategies. When the team's ability to identify the correct solution is weak, frequent early perturbations can result in increased divergence in feedback among teams. The presence of conflicting advice from other teams exacerbates the challenges faced by actors in making informed judgments based on feedback.

1. Introduction

Research and product development projects are becoming increasingly complex. A single team simply cannot handle such complex tasks. The successful completion of the exploration within the given time frame required effective collaboration among multiple interdisciplinary teams. The Boeing 777 airliner, for instance, was developed by a whopping 251 teams, while the Airbus A380 had hundreds of teams from France, Germany, the UK and Spain working on it. Many teams face the situation where their members come from different R&D organizations, representing various areas of knowledge, and are tasked with solving complex problems using groundbreaking approaches (Edmondson and Nembhard, 2009, Majchrzak et al. 2012, Bruns, 2013, Ben-Menahem et al. 2016, Ávila-Robinson and Sengoku, 2017; Bergenholtz et al., 2023). The actors need to innovate and make breakthroughs in their respective subdivisions, while also ensuring that the entire system maintains sufficient stability and efficiency after integrating various subsystems. The trade-off between the two continues to puzzle many researchers and engineers.

The reason "decision makers miss the forest for the trees" is that they do not fully understand the interdependence of choices

^{*} Correspondence to: College of Economics and Management, Taiyuan University of Technology, NO.79, Yingze West Main Street, Taiyuan, Shanxi 030024, China.

E-mail addresses: nksy11master@163.com (J. Mi), dongjiamin@csu.edu.cn (J. Dong).

^{1 0000-0001-7682-2033}

(Clement, 2023). In R&D and innovation projects with highly interdependent subsystems, decision makers find it difficult to predefine optimal goals for individual tasks. The program adjustments made by any team will directly impact the achievement of each sub-goal and the overall goal (Hu and Bettis, 2018). In order to address complex problems, each actor needs to explore the combination that is most beneficial to all parties involved and the system as a whole, rather than simply choosing the combination that is most beneficial to themselves. This requires each actor or team to continuously adapt their choices based on the choices of other teams, which is known as coupled exploration (Knudsen and Srikanth, 2014; Ben-Menahem et al., 2016; Olsen et al., 2016; Baumann et al., 2019; Ghosh and Wu, 2023; Park et al., 2024; Srikanth and Ungureanu, 2025). For example, the parameters of each component of an aeroengine, such as weight, size, shape, and strength, affect the functional realization of the other components. Thousands of components are equipped together and interact with one another in the same small space. From a physical space perspective, the decision to increase the thickness of a part by 0.1 mm can impact resonance frequencies in certain areas, temperature limits, airflow direction and overall weight, necessitating changes in shape, volume and material selection for other parts. From the perspective of thermal conduction, the operational temperature of an aero-engine not only impacts turbine blades and combustion chambers but also exerts certain influences on the fuel distribution system, ignition system, lubrication system, and exhaust system. When the temperature of the combustion chamber increases by 20 degrees Celsius, there is a risk of turbine blade collapse and potential failure in the lubrication system. Therefore, the optimal choice for one team is not necessarily the optimal choice for the entire system.

The Boeing 737 Max once caused serious accidents due to complex coupling and mismatch issues within its system. In response to competition from the Airbus A320neo, Boeing hastily modified the 737 model. The Boeing 737 Max was delivered in 2017, but shortly after delivery, several severe air crashes occurred. In 2018, the Lion Air crash in Indonesia claimed 189 lives, and in 2019, the Ethiopian Airlines crash killed 157 people. The fundamental cause of these accidents was that the technical team ignored the coupling between various components of the entire aircraft system. The 737 has a low fuselage, while the upgraded LEAP-1B engine is larger in size. Engineers moved the engine forward and upward and extended the landing gear by eight inches, causing the 737 Max to have an off-center gravity and a large angle of attack during flight. Technicians installed the MCAS system on the 737 Max; however, a malfunction of the angle-of-attack sensor could output incorrect data, causing the aircraft to enter a dive that led to crashes.

In coupled exploration, because changes in the choices of one team can also impact the achievement of the goals of the other teams, the teams need to repeatedly exchange views on the areas they are exploring together (Levinthal, 1997; Baumann and Siggelkow, 2013; Knudsen and Srikanth, 2014; Baumann et al., 2019). Due to the actors' bounded rationality, they can search for the optimal decision within their own field of vision but are unable to search for the optimal decision on a global scale. Their perceived optimal decisions may render their sub-goals unattainable for the other teams associated with them. Communication issues among teams can give rise to cognitive biases and create confusion regarding goals. During the later phase of system integration, teams often encounter challenges and find themselves repeatedly adjusting parameters, resulting in delays to the delivery date. Therefore, it is imperative to focus on and reconsider the information transmission, feedback, and coordination mechanisms among multiple teams (Siggelkow and Rivkin, 2009, Baumann and Siggelkow, 2013, Knudsen and Srikanth, 2014, Ben-Menahem et al. 2016, Baumann et al. 2019, Jafari Songhori and Nasiry, 2020, Jafari Songhori et al. 2020; Clement, 2023).

When a team makes new decisions, it is crucial to effectively communicate those decisions to other teams as they directly impact the achievement of their respective goals. Other teams cannot immediately make a judgment on new decisions when they receive new information, as they also need to conduct a series of experiments to determine whether the solution aligns with their own optimization goals. To enhance global optimization, it is essential for any team to receive feedback from other teams. However, feedback from collaborators is not always reliable, and it can potentially mislead actors when it is ambiguous or even incorrect. The actors are not deliberately providing inaccurate feedback to other teams. Some studies have found that high-frequency feedback over a short period is not conducive to discovering optimal solutions, and an excessive pursuit of real-time feedback can even stifle creativity (Chen et al., 2020; Mertens et al., 2021; Asplund et al., 2022). Researchers are limited in their ability to provide a completely accurate assessment of decisions that fall outside their own area of expertise (Chen et al., 2020; Billinger et al., 2021). The situation is further aggravated by cognitive constraints and limited perspectives. Other teams may mistakenly evaluate the incorrect solution as the correct one, or the correct solution as incorrect. Incorrect feedback can lead the decision maker to either abandon the correct choice or adopt an incorrect one.

In coupled exploration, individuals need to send information about current and new solutions to other teams, and these teams will provide feedback upon receiving the information. Feedback often takes the form of questions and suggestions (Baird et al., 2000; Harrison and Rouse, 2015; Toivonen et al., 2023; Van Werven et al., 2023). These recommendations can sometimes exert coercive pressure, compelling the actor to abandon their initial choice or even alter the original technical trajectory (Knudsen and Srikanth, 2014; Burnell et al., 2023). We use the term "perturbation" to refer to this process. If the space to be explored by the actors is likened to rough terrain, then the height of each point represents the performance of each potential solution (Levinthal, 1997; Baumann and Siggelkow, 2013). Each actor searching for the global peak in the rugged fitness landscape is likely to be influenced by the feedback from closely related teams, potentially leading to a deviation from their original exploration path. The perturbation can sometimes cause the team to abandon the right technical direction (Ter Wal et al., 2023), but in many cases it can also spark new inspiration and creativity (Kim and Kim, 2020; Mannucci and Perry-Smith, 2022). When the team informs the other team of the revised proposal, these new options may lead to inconsistencies and require new feedback between the teams, which could cause additional perturbations for the other team.

Perturbations arise when teams hold discordant perspectives, and the frequency and timing of questioning impact the exploratory behavior of other teams. As the exploration progresses, the communication patterns between the teams are also changing (Song et al., 1998; O'Reilly and Binns, 2019; Kim and Kim, 2020; Clement, 2023). The question we need to analyze is: What perturbation frequency is most beneficial for each team in coupled exploration? Should the frequency of perturbations change dynamically during the early,

middle, and late phases of coupled exploration? Do frequent perturbations in the early stages permanently alter the path selection in coupled exploration? The timing of perturbations may play a crucial role in the feedback loop of coupled exploration. To address these issues, we have developed a multi-agent simulation model. The next step involves conducting an in-depth analysis of the relevant literature and simulation results.

2. Literature review and research questions

2.1. Multiple effects of feedback

The significance of feedback in the coordination mechanism: To achieve coordination, actors must establish effective communication and information processing mechanisms (Tushman and Nadler, 1978; Baumann et al., 2019; Mertens et al., 2021; Clement, 2023). Effective completion of interdependent work relies on the transmission and feedback of information across departments and teams, from an information processing perspective. Each team should share relevant details and provide constructive input to the other teams regarding the new solution. This includes providing feedback on whether the other team's solution improvements align with the overall goal, identifying any challenges faced by the other team in their decision-making process, and suggesting areas for further improvement. Each team serves as both a source of new information and a recipient of feedback from the other teams. Feedback plays a crucial role in team development as it aids in the accumulation of experience through experimentation as well as continuous improvement (Joseph and Gaba. 2020).

The choice that appears right may not necessarily be the best option for the entire system. Throughout the development process, teams are required to exchange information regarding various parameters and obtain feedback from other teams. The effective utilization of external feedback can facilitate the team and organization in modifying the technical solution (Gavetti et al., 2012). Frequent communication and feedback serve to mitigate common confusion in collaborative exploration (Puranam et al. 2012, Knudsen and Srikanth, 2014). According to Puranam and Swamy (2016), increasing the frequency of feedback reduces the likelihood of individuals misleading each other during the coupled search process, thereby resolving the initial mutual misunderstanding. Receiving continuous feedback constantly shapes and refines design ideas, serving as a catalyst for new experimental approaches (Cardinal et al. 2011, De Stobbeleir et al. 2011, Harvey and Kou, 2013).

The feedback from others, particularly in the context of groundbreaking work, has the potential to ignite inspiration and foster unexpected innovations (Perry-Smith and Mannucci, 2017, Mannucci and Perry-Smith, 2022, Toivonen et al. 2023).

Feedback and consensus: Minimizing internal conflict and maximizing consensus within the team is crucial (Van de Ven, 1986, Harvey, 2013). The provision of feedback is not a unidirectional transmission of information, but rather emerges from the iterative interaction process among participants engaged in innovation activities. The participants collaboratively develop a cohesive plan through iterative feedback processes (Harrison and Rouse, 2015). The process of mutual correction through feedback facilitates the formation of consensus, while simultaneously fostering knowledge convergence among participants. The presence of diverse groups is more likely to give rise to divergent perspectives, yet these divergences also serve as catalysts for fostering creativity. The groups that exhibit cognitive convergence, although capable of reaching consensus more efficiently, encounter difficulties in generating solutions that transcend existing frameworks (Harvey, 2014, Hoever et al. 2018). The pursuit of ideas that align with prevailing social norms prompts individuals to consistently take into account feedback from peers before taking action (Rogers and Adhikarya, 1979). Repetitive communication prompts teams to eventually pursue solutions that are more amenable to one another, while discarding those that deviate from convention or appear excessively intricate. Ultimately, all parties tend to settle for a suboptimal outcome that satisfies their respective interests but fails to achieve the overall optimal solution.

Negative feedback: Experts often demonstrate proficiency and accuracy in evaluating domains within their expertise, yet they tend to exhibit fallibility or bias when assessing alternative solutions that involve radical innovation, particularly those outside their familiar purview (Knudsen and Levinthal, 2007; Chen et al., 2020; Asplund et al., 2022). Under time constraints, the efficiency of actor information processing may be compromised, leading to potential inaccuracies in evaluation and consensus formation (De Dreu, 2003, Blair and Mumford, 2007). Receiving negative feedback can enhance recipients' awareness of the existing gaps and inadequacies in solutions, thereby motivating them to adopt more effective and innovative strategies. However, some studies have found that comments from colleagues or other teams can sometimes hinder the creativity of the entire project team due to their overly cautious, subjective, or biased nature (Girotra et al. 2010; Chen et al., 2020; Kim and Kim, 2020).

Conflict with feedback: Whether it involves transmitting new information or providing feedback, their role is to resolve conflicts, clarify confusion, and ultimately facilitate agreement among all parties involved (Hauptman and Hirji, 1999). However, in certain instances, the feedback not only failed to achieve consensus but also led to collective confusion and ultimately worsened conflicts. Actors from diverse disciplinary backgrounds possess varying understandings of the problem's framework and objectives, which hinders the integration of their information and increases the likelihood of conflicts (Cronin and Weingart, 2007). The actors are actively identifying the shortcomings of the opposing team and providing justifications for their own decisions. Although each person is reluctant to change their existing plan, they attempt to persuade the other partners to modify the plan according to their own preferences. This heated brainstorming actually conceals underlying acrimony. These ostensibly positive communications have resulted in heightened conflict.

2.2. Mutual perturbations in coupled exploration

As the R&D project life cycle progresses, communication styles within the team also exhibit variations, including temporary

perturbations to the work of other teams and direct comments (Baird et al. 2000). The innovation participants receive questions from feedback providers, which may include their confusion regarding the existing solution. Feedback from other teams is often in the form of questions and suggestions, commonly using phrases such as "why...", "You should...", "You need...", and "You'd better put..." (Harrison and Rouse, 2015). Furthermore, suggestions from other teams may encompass negative sentiments, adverse remarks, and even constructive criticism. In response to these unavoidable recommendations, the team must make adjustments to their protocols, resulting in a deviation from the original trajectory of exploration. This process is referred to as perturbation. The presence of perturbations caused by other teams may impede the pace of development and even result in a deviation from the initial objective; however, these interactions significantly enhance the caliber of innovative work (Toivonen et al. 2023).

In many instances, inadvertent actions lead to perturbations that have adverse consequences. Feedback providers do not intentionally avoid important issues and pass difficult ones onto other teams because they are uncertain about the impact of their opinions and suggestions on those teams. The individuals who possess the most comprehensive understanding of their respective solutions are those within their own team. The actors may feel overwhelmed and perplexed when confronted with inquiries and suggestions for improvement from other teams. Furthermore, the influx of suggestions from external sources can lead to information congestion, thereby increasing the difficulty in selecting appropriate suggestions and reducing decision-making efficiency (Piezunka and Dahlander, 2015). The excessive information generated during coupled exploration will occupy a significant amount of cognitive resources for the actors, thereby impacting their judgment and potentially leading them into a state of chaos.

Novel innovations and solutions often encounter rigorous scrutiny from external stakeholders (Ter Wal et al. 2023; Van der Voet, 2023). The introduction of innovative and imaginative solutions may also attract intense scrutiny and unfavorable criticism. Negative suggestions and reviews can pose a challenge to the feasibility of the original idea, potentially compelling the innovator to revise or abandon their proposal at a later stage (Mainemelis, 2010, Grimes, 2018, Fisher et al. 2018). The technical teams are faced with the challenge of expending significant effort in addressing doubts from other teams and even contending with unreasonable suggestions amidst disruption (Rahman and Barley, 2017). Receiving negative feedback triggers a period of turbulence in the innovation process, compelling innovators to reassess ideas, discard ineffective ones, revise plans, and seek re-evaluation (Toivonen et al. 2023). This sequence of events has the potential to propel creative work towards new and even radical directions; however, it can also result in mediocre final solutions. In light of this series of studies, we pose the initial inquiry:

Question 1. In coupled exploration, at what frequency should the perturbation occur?

2.3. Communication behaviors at different stages

Early stages of coupling exploration: In the initial stages of coupling exploration, actors possess an incomplete understanding of the problem space, and it is only through iterative interaction and feedback that they can gain comprehensive insights into all potential solutions (O'Reilly and Binns, 2019; Clement, 2023). In the early stages, each R&D team was unable to fully understand the technical details of other closely related subsystems. Teams at this point are unable to identify the optimal target area within their own subsystems, leading to unclear and ambiguous information being provided to the collaborating teams (Knudsen and Srikanth, 2014). The transformation of a creative yet immature idea into an implementable solution requires extensive feedback and technical support from colleagues or other departments (Chen et al., 2020; Ter Wal et al. 2023). The significance of early feedback cannot be undermined; however, it may prove to be counterproductive in certain circumstance (Burnell et al., 2023). Due to the unstructured nature of the

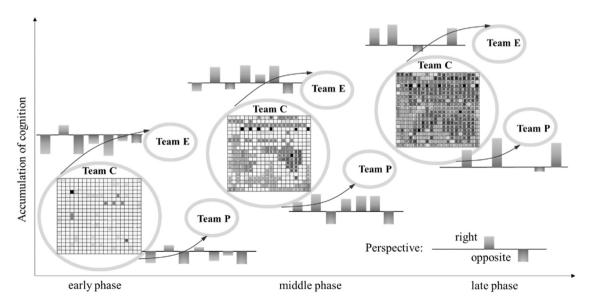


Fig. 1. Different stages of multi-team exploration.

problem and the ambiguity of the parameters, early information shared among developers contained many errors that could slow down the project (Reid and De Brentani, 2004). Premature misinformation can interfere with other teams' exploration paths (Baumann et al., 2019). Furthermore, external evaluators may perceive novelty and utility as conflicting concepts, potentially harboring hidden biases against innovation that could hinder their support for bold ideas and radical initiatives proposed by others (Mueller et al. 2012, Piezunka and Dahlander, 2015). Fig. 1 is a schematic diagram of different stages.

Middle stages of coupling exploration: At this stage, each team has mined its field more thoroughly and roughly determined the path to the optimal choice (Knudsen and Srikanth, 2014). Since each team has already explored the subsystems they are responsible for in depth, they have accumulated a great deal of knowledge. In horizontal communication, more accurate and valuable information is exchanged between different teams. In the mid-stage, perturbations from other teams can help explorers uncover legacy issues earlier and enable team members to explore previous alternatives in response to suggestions or questions from feedback providers (Knudsen and Srikanth, 2014; Harrison and Rouse, 2015). This set of processes makes the mid-stage of exploration a critical stage for making major discoveries (Golder et al., 2009; Mainemelis, 2010; Harrison and Rouse, 2015; O'Reilly and Binns, 2019; Mi et al., 2023; Park et al., 2024). Comments and suggestions from other teams at this time may interfere with the original exploration model, causing the team to deviate from the current exploration path (Grimes, 2018; Fisher et al., 2018; Kim and Kim, 2020; Ter Wal et al., 2023). The flood of questions and suggestions also creates information overload, which takes up developers' time and makes it harder for them to make sound judgments (Baird et al., 2000; Piezunka and Dahlander, 2015; Harrison and Rouse, 2015).

Late stages of coupling exploration: In the later stages, the joint participation of multiple departments and teams will also play a significant role in promoting product innovation, but this promotion mechanism is quite different from the early cross-departmental intervention (Pateli and Lioukas, 2019). According to Harrison and Rouse (2015), "excavations" are observed during the initial phases of a creative project and involve substantial modifications to crucial aspects of the prototype, whereas readjustment takes place in the later stages. Rubenson and Runco (1992) and Yuan and Zhou (2008) found that in the early stage of creative work, external evaluation will lead to the limitation of new ideas, but in the later stages of creative work, especially in the stage of product modification and improvement, suggestions from other teams help developers improve the reliability and rationality of technical solutions.

According to Song et al. (1998), their analysis of the research and development process of 16 Fortune 500 enterprises revealed that blindly promoting the integration of viewpoints and functions from different teams at all stages of new product development does not actually foster innovation; Instead of mandating cross-team integration at all stages of a new product's development, it is more effective to implement specific stages for cross-team integration patterns. This highlights the necessity for each team to allocate a specific duration of autonomous exploration time during all stages of development, as congregating them together for an excessive number of discussions would yield counterproductive outcomes. In reality, not all instances of intensive communication and

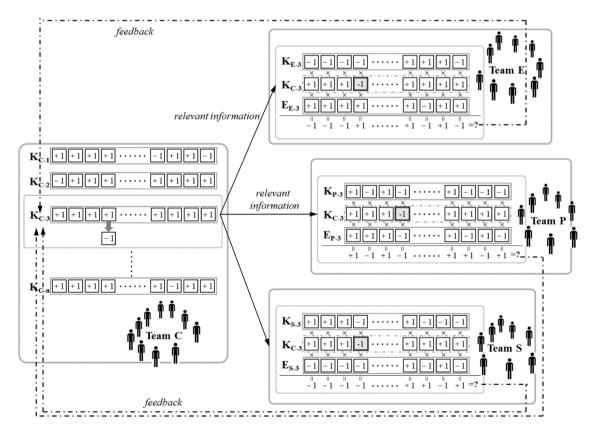


Fig. 2. Process of coupled exploration.

interaction during the development process yield positive outcomes. There are two prevalent modes of communication: the first involves actors who share a common workplace and engage in frequent interactions, while the second entails actors working independently for a certain period and subsequently exchanging ideas. The first model was found to be insufficient in generating a sufficient quantity and quality of high-quality ideas, as evidenced by empirical investigation, when compared to the second model (Girotra et al. 2010). Excessive communication diminishes the extent of thorough investigation, and actors must periodically disconnect and uphold autonomous exploration (Bernstein et al. 2018; Mi et al. 2024). The aforementioned series of studies prompts us to contemplate an additional inquiry:

Question 2. Is it necessary to dynamically adjust the frequency of perturbation during the process of coupling exploration?

3. Model

The multi-agent computational simulation method is well-suited for analyzing human interaction, collaboration, and learning processes. We use a multi-agent simulation model to conduct this study. All our simulations are developed and programmed by Repast Simphony 2.10.0. Repast Simphony was created at the University of Chicago. Subsequently, it has been maintained by organizations such as Argonne National Laboratory in Illinois, USA. Our research model is developed using the Java language.

The exchange of information is a fundamental aspect for any team, as it assumes the dual roles of both sender and receiver. The tuple K represents the actor's beliefs, while the tuple E signifies the objective environment that necessitates exploration. As depicted in Fig. 2, the tuple $K_{C\cdot3}$ of Team C exerts influence on the beliefs of other teams, including but not limited to team E's tuple $K_{E\cdot3}$, team E's tuple $E_{C\cdot3}$ and team E's tuple $E_{C\cdot3}$ in our model, the extent to which team E can comprehend the $E_{C\cdot3}$ aligns with the true $E_{C\cdot3}$ with a 50 % probability; thus, team E's independent exploration fails to capture the complete essence of the $E_{C\cdot3}$. Hence, Team E should seek feedback from other teams to further explore $E_{C\cdot3}$. Teams E, E, and E rely on Team E to provide them with updated information regarding design and parameter tuning. The constant feedback from teams E, E, and E is indispensable for Team E.

Consider Team C, where K_{C-1} , K_{C-2} , ..., K_{C-n} represent the cognitive beliefs of its members regarding the subsystems they are accountable for. Here, n denotes the total number of teams and their corresponding responsibilities, implying that Team C's cognition is interconnected with n-1 other teams. The tuple K_{C-j} consists of m components, each composed of randomly generated numbers -1 or 1. For example, $K_{C-3} = (1, 1, 1, 1, ..., 1, 1, 1)$. The symbols E_{C-1} , E_{C-2} , ..., E_{C-n} represent the theoretically optimal values of the subsystems. For instance, E_{C-3} is defined as (1, 1, 1, -1, ..., -1, 1, -1, -1). The team C consists of 25 members. In the context of the tuple K_{C-3} , if 15 members hold a belief that the value for this dimension is 1, while the remaining 10 members believe it to be -1, then a value of 1 signifies team C's perspective on the first dimension of K_{C-3} .

The performance of team C's exploration can be assessed through the comparison between K_C and E_C . For instance, the value of $1 \times 1 + 1 \times 1 + 1 \times 1 + 1 \times (-1) + 1 \times (-1) + 1 \times (-1)$ denotes the degree of correspondence between K_{C-3} and E_{C-3} . The goal of Team C's exploration is to bring the value of K_C closer and closer to that of E_C . The cognition of team E, team P, and team S in dimensions K_{E-3} , K_{P-3} , and K_{S-3} is influenced by the presence of team C, as depicted in Fig. 2. Therefore, they require information pertaining to K_{C-3} . The performance of team E in the E-3 dimension can be quantified by evaluating the match degree between $K_{E-3} \cdot K_{C-3}$ and E_{C-3} , which is represented as the value of $-1 \times 1 \times 1 + (-1 \times 1 \times 1) + (-1 \times 1 \times 1) + ... + 1 \times 1 \times 1 + (-1 \times 1 \times 1)$.

 Q_f : At some point, Team C sends information about K_{C-3} to Team E; for example, Team C changes the value of the fourth element in the tuple K_{C-3} from 1 to -1. The Team E received information regarding the K_{C-3} and commenced a re-exploration of the K_{E-3} . After a certain period of time, if the value of K_{E-3} · K_{C-3} · E_{E-3} exceeds its previous level, Team E will provide positive feedback to Team C. Conversely, if the value decreases, Team E will offer suggestions to modify K_{C-3} . If the majority of other teams provide negative feedback for Team C, then it is necessary for Team C to revise K_{C-3} . The aforementioned process refers to the perturbation in coupling exploration. The aforementioned process refers to the perturbation in coupled exploration, with its frequency denoted as Q_f . If the other team consistently does not raise any questions or provide feedback about the K_{C-3} , then the Q_f value is 0. A Q_f value of 0.01 indicates that there is a 0.01 probability for agents to provide feedback and ask questions in each cycle.

 C_p : The exploration mechanism within each team in our model aligns with March's (1991) social learning model. The concept of C_p denotes the velocity at which actors discern superior solutions and achieve optimal consensus. The beliefs of agent i regarding E_{C-2} will gradually align with those of agent j if agent i acknowledges that agent j outperforms him in the K_{C-2} tuple. In the model, each dimension in the tuple moves closer to the tuple of the superior individual with a probability denoted as C_p . The process entails the utilization of interpersonal learning within the team to meticulously select and code the optimal choice (March, 1991, Miller et al. 2006, Kane and Alavi, 2007, Posen et al. 2013, Miller and Lin, 2015). The team can only convey a definitive message about a solution to the other teams involved once its members have reached a consensus. The relevant parameters are listed in Table 1.

Fig. 2 only depicts the information exchange among the four teams at a specific moment in time. Team C is not always the sender of

Table 1Key model parameters.

Parameter	Definition	Range of Possible values 25(Always fixed)		
n	Number of subsystems and teams			
m	The number of elements in a tuple	25(Always fixed)		
w	The number of team members in each team	25(Always fixed)		
Q_f	The frequency of perturbations among teams	(0,1)		
C_p	The speed of proposal screening and consensus building	(0,1)		

the initial message and the recipient of the feedback. In dimensions other than K_{C-3} , such as K_{C-5} and K_{C-7} , Team C also relies on information from other teams and provides feedback based on its own exploration performance. Each team serves as both the executor of the exploration and the assessor of other teams. Assuming there are n sub-systems within the system, each subsystem is interconnected with the others, and each team is accountable for one subsystem. The performance of collaborative exploration is measured by averaging the performances of all teams.

4. Simulation results and analysis

Fig. 3 illustrates the time-dependent variation curve of coupling exploration performance under different perturbation frequencies. The figure on the left indicates that when the perturbation frequency is high $(Q_f = 0.07)$, the exploration process will exhibit more twists and turns. In each perturbation, the performance exhibits small oscillations back and forth, posing challenges to maintaining a sustained and rapid growth trend in coupled exploration. Under the low perturbation frequency $(Q_f = 0.01)$, after an initial increase in performance, the performance curve remains relatively stagnant for a prolonged period of time and appears to be flat. The performance of coupled search can continue to improve and reach a high level when the perturbation frequency is moderate $(Q_f = 0.04)$. The figure on the right demonstrates that both excessively high and excessively low perturbation frequencies are detrimental to the growth of coupled exploration performance. The optimal range for Q_f in coupled exploration is typically between 0.03 and 0.05. It is worth noting that the optimal value of Q_f holds limited practical significance, as it is also influenced by various other parameters. The optimal value of Q_f may exhibit heterogeneity under varying exploration modes (Miller et al. 2006, Posen et al. 2013, Knudsen and Srikanth, 2014) and social relationship structures (Fang et al. 2010, Kim and Anand, 2018, Mi et al. 2023). In the subsequent simulation experiment, we will analyze the synergistic impact of C_p and Q_f on the coupled exploration.

The perturbation changes over time in Fig. 4, illustrating several typical cases. Cases 1 and 2 represent high and low perturbation frequencies, respectively. Case 3 demonstrates high perturbation frequencies in the early stage followed by low perturbation frequencies in the later stage. Case 4 exhibits low perturbation frequencies initially and high perturbation frequencies subsequently. The perturbation frequency in case 5 is initially low, followed by a sustained high level during the middle stage, and finally returns to a low level in the late stage. The frequency of early and late perturbations is higher in case 6, whereas the frequency of mid-stage perturbations is comparatively lower.

The influence of coupling exploration performance varies greatly depending on the frequency of perturbation, as illustrated in cases 1 and 2 in Fig. 5. A C_p value of 0.05 indicates a weak ability of the team to select excellent schemes and reach a consensus. Based on simulation results, frequent perturbations in this case will result in significant deviation from the original goal of coupling exploration. When C_p has a value of 0.2, frequent perturbations not only do not hinder the collaborative search activity but also expedite all agents' discovery of the optimal choice. By comparing case 1 and case 2, it can be observed that when the value of C_p is very high, frequent perturbations can assist the actor in quickly selecting the optimal scheme and avoiding repeated corrections in the subsequent stage. At the same time, we also found that when there are frequent perturbations between teams, the performance of coupled exploration becomes highly sensitive to the value of C_p . Based on scenarios 1 and 2, we have derived the following conclusions:

Ha. : If the team quickly forms the correct consensus, frequent perturbations from other teams enhance the efficiency of coupled exploration. However, if the team takes a long time to form the right consensus, frequent perturbations from other teams can disrupt the process of coupled exploration.

Case 3 demonstrates that frequent perturbations in the early stages significantly amplify the sensitivity of coupled exploration behavior to changes in the team's learning ability C_p . These perturbations not only impact current exploration performance, but also have long-lasting effects on exploration behavior. Although the frequency of perturbations decreases in the middle and late stages, there is still a significant disparity in the performance of coupling exploration. The observation in case 4 demonstrates that even with a low C_p value, the presence of low-frequency perturbations during the early and middle periods can lead to a sustained increase in

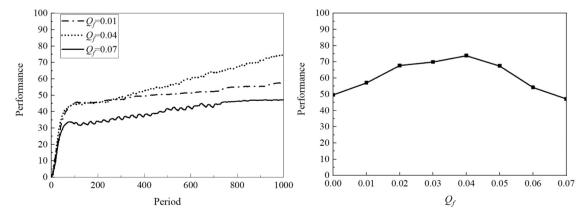


Fig. 3. Influence of Q_f on coupled exploration, $C_p = 0.15$.

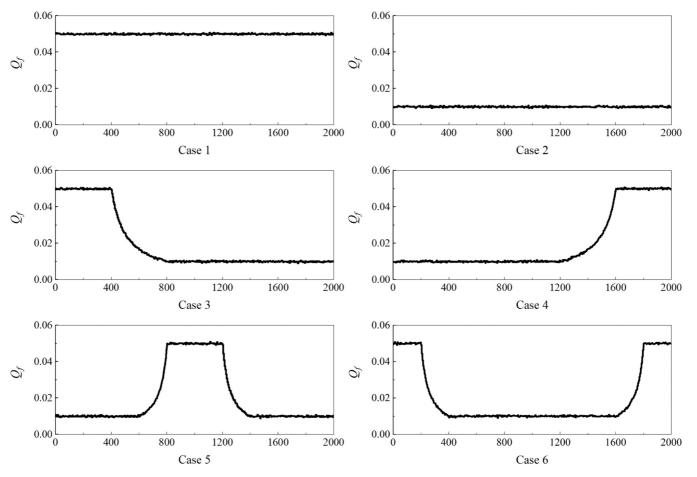


Fig. 4. Typical cases of perturbations changing with time.

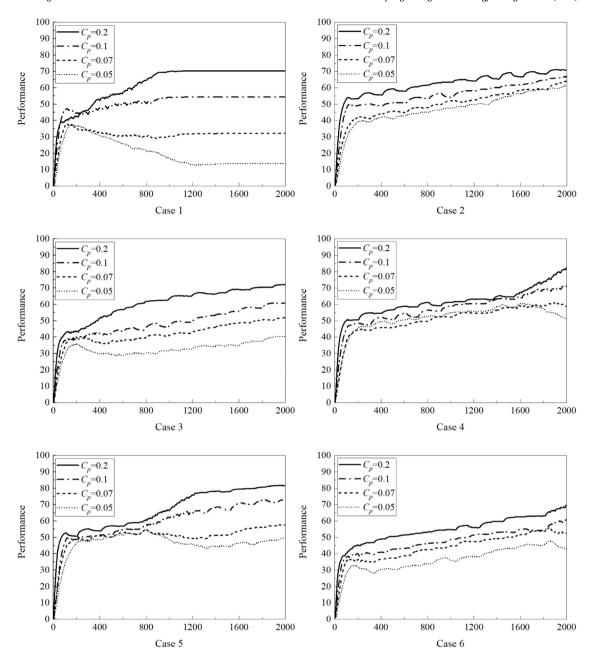


Fig. 5. The impact of dynamic variation in Q_f on the coupled exploration.

exploration performance. In the later stages, frequent perturbations can result in accelerated growth in exploration performance; however, this necessitates a team with robust internal screening capabilities. If the team lacks the ability to efficiently and accurately sift through the available options, frequent perturbations instead hinder their collaborative exploration behavior, leading to incorrect decision-making by the agent. The following conclusions are drawn when comparing Case 3 and case 4:

Hb. : Frequent perturbations during the early stage induce permanent alterations in the trajectory of coupling exploration throughout the middle and late stages. The later stages of coupled exploration will witness significant improvements through frequent perturbations, provided that each team possesses a strong ability to make optimal choices.

The comparison of Case 5, Case 3, and Case 1 reveals that frequent perturbations during the intermediate stage of coupling exploration leads to optimal performance attainment by the agents. The growth rate of coupled exploration in case 5, although slower than that in case 1, still surpasses the rate observed in Case 3 and attains higher equilibrium performance during the later stage. Compared to case 2 and case 4, case 6 does not have any significant advantage. The observation suggests that introducing frequent

perturbations in both early and late stages may not necessarily facilitate the search for the optimal choice. However, the equilibrium performance of case 6 did not exhibit significant differences or polarization under varying C_p values. We have reached the following conclusions:

Hc. : The coupling exploration model with frequent perturbations in the early and late stages has a higher level of fault tolerance and wider application. Mutual perturbations between teams in the middle stage stimulate performance growth potential in the later stage, but it requires each team to quickly sift through the correct choices.

Based on the aforementioned findings, it is imperative to further contemplate the correlation between Q_f and C_p , as well as explore potential underlying factors contributing to these observed outcomes. Firstly, agents are often overwhelmed with excessive information due to the frequent suggestions and opinions from other teams, resulting in information overload. When other teams raise questions and suggestions, it compels the team to reassess the previous plan, identify any shortcomings, and subsequently revise it while experimenting with a new approach, thereby imposing an additional cognitive burden on them. If agents are overwhelmed with an excessive amount of information, they may experience cognitive overload, leading to the misjudgment of a wrong choice as the right one (type I error) or the rejection of an otherwise correct choice (type II error).

Second, the success and enhanced performance in teams rely on a complex interplay among different contributing factors. If multiple elements are modified simultaneously, it becomes difficult for the team to determine which specific element's improvement has contributed to the overall performance enhancement, leading to certain challenges for agents. For instance, at time t, Team C modified the third element of K_{C-3} from -1-1 and changed the tenth element from 1 to -1 at time t+10. Let's assume that team C made the correct decision at time t, but an incorrect one at t+10. For some time after t+10, Team C will receive feedback from other teams; however, this feedback will not enable Team C to determine which of the previous choices was correct. The modification of the third element of K_{C-3} leads to a performance improvement, which offsets the performance decrease caused by the modification of the tenth element.

Third, the feedback from other teams will vary for the same solution improvement. A minor alteration may result in conflicting recommendations from different teams, thereby exacerbating the challenge of decision-making for the agents. Frequent early feedback is more likely to result in dissonance between teams, and this dissonance is not limited to those who provide feedback and those who receive it. During the same time period, agents may receive both positive and negative feedback from other teams, thereby complicating the judgment process. After receiving feedback, each team is required to complete a larger volume of trial and error work within a shorter timeframe, thereby increasing the likelihood of making mistakes. The ability to efficiently evaluate and select appropriate solutions, as well as foster consensus within a team, not only impacts its own performance but also influences the overall consensus among teams. If the team fails to promptly identify an appropriate solution, it will lead to significant discrepancies in the evaluation of the same solution by other teams. Teams engaged in parallel engineering tasks or distributed R&D teams encounter challenges in expeditiously reaching consensus, thereby exacerbating the intricacies of the exploration process.

When interdisciplinary teams convene to address problems, divergent perspectives and potential conflicts often arise due to disparate objectives and knowledge frameworks. For instance, the aerodynamics team aimed to increase the surface area of the turbine blades for better air intake, while the materials team strived to maintain a reasonable diameter range to prevent blade fracture. Therefore, when the design team of the engine turbine proposes reducing the size of turbine blades, the aerodynamics team will provide negative feedback, while the materials team may offer positive feedback. When the team responsible for the engine combustion system proposes an additional increase of 50 °C in the maximum operating temperature, the team handling turbine blade materials may provide dissenting feedback, while the team dealing with fuselage materials may offer affirmative feedback. The team responsible for the development of fuselage materials favored the improvement because it had the potential to enhance thrust capabilities, thereby alleviating the stringent weight requirements imposed on the aircraft's fuselage. Several studies have demonstrated that certain divergences in opinions can be advantageous as they foster diverse thinking and encourage the team to reexamine the problem (March, 1991, Jehn, 1995). However, due to divergent interpretations of the problem among the teams, the presence of diverse perspectives can exacerbate conflicts, thereby impeding consensus-building among all parties involved (Cronin and Weingart, 2007, Harvey, 2013). To further elucidate the factors contributing to the divergent outcomes depicted in Fig. 5, we will undertake an additional supplementary simulation experiment for comprehensive analysis.

The dissimilarity index, represented by Eq. (1), is employed to quantify the varied perspectives and feedback from different teams regarding the same issue. The symbol Δg_i indicates that team i has received the message that the most recent change in strategy can enhance the exploration performance of the other party. For example, the fourth value in the tuple K_{C-3} is modified by team C, changing it from 1 to -1. Team B is informed about this change and instructed to continue exploring K_{B-3} . The value of $K_{B-3} \cdot K_{C-3} \cdot E_{B-3}$ will be compared to the previous value, and if it has increased, Team B will provide positive feedback to Team C after a certain period of time. Out of the n-1 other teams, if all 9 teams give positive feedback to Team C, then Δg_i will be equal to 9. If 10 other teams responded to team C by stating that changing the fourth value of tuple K_{C-3} from 1 to -1 resulted in a deterioration of performance in the other system, then Δr_i would be equal to 10. If 5 other teams perceive that the last choice or improvement made by Team C has no impact on their respective subsystems, then the value of Δu_i is 5.

$$\text{Dissimilarity} = \frac{1}{n} \sum_{i=1}^{n} \frac{\Delta g_i(\Delta r_i + \Delta u_i) + \Delta r_i(\Delta g_i + \Delta u_i) + \Delta u_i(\Delta g_i + \Delta r_i)}{(n-1)(n-1-1)} \tag{1}$$

The denominator of Eq. (1) consists of two components: (n-1), which represents the number of relevant teams other than itself, and (n-1-1), which signifies the comparison between the perspectives of each team participating in the feedback and those of the other

teams involved. For instance, when team C receives feedback from 24 other teams with $\Delta g_i = \Delta r_{i=} \Delta u_i = 8$, it results in the highest dissimilarity index of feedback. Conversely, when $\Delta g_i = 24$, $\Delta r_i = 0$, $\Delta u_i = 0$ or when $\Delta g_i = 0$, $\Delta r_i = 24$, $\Delta u_i = 0$, the dissimilarity index of feedback is minimized. The variation of feedback dissimilarity index across different cases is illustrated in Fig. 6.

The choice is deemed correct if 13 out of the remaining 24 teams provide positive feedback, while the remaining 11 teams offer negative feedback. After receiving positive feedback, teams will no longer overturn choices they believed were correct (but actually wrong); instead, they will continue to revise choices that received negative feedback from other teams. Due to the coupling of complex systems, making the correct choice may elicit unfavorable feedback, potentially leading agents to misjudge their decisions and resulting in the occurrence of type II errors (Knudsen and Levinthal, 2007). Even though agents may make choices that do not align with global optimization, the performance of certain teams is temporarily enhanced, resulting in the preservation of these suboptimal decisions, which are commonly referred to as type I errors (Denrell and March, 2001, Puranam and Swamy, 2016). In Case 1, teams reach a consensus on a suboptimal outcome in advance, thereby eliminating any differences in views at a later stage. This phenomenon occurs because the two types of errors rapidly accumulate in the early stage, with the second type of errors appearing in large numbers before the first type. By the mid-to-late stage, each team no longer modifies their perception of what is considered as the correct solution, resulting in a cessation of information exchange regarding new modifications.

The comparison of Case3 with Case4 and Case5 with Case6 reveals that if frequent perturbations occur during the initial phase of coupling exploration, there will be significant variations in inter-team feedback. Conversely, when frequent perturbations arise during

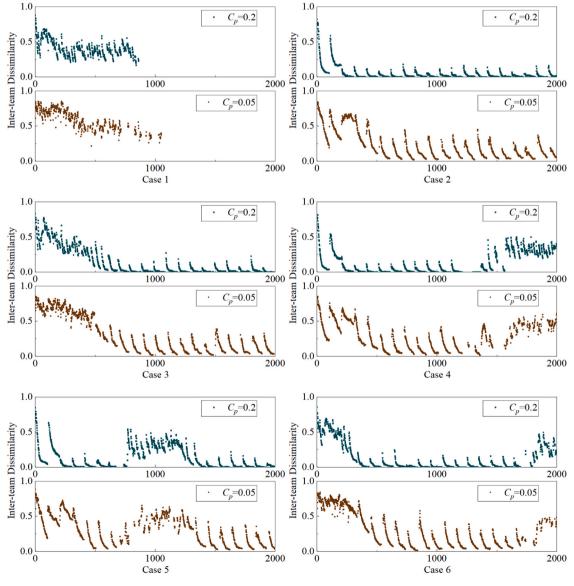


Fig. 6. Changes in the diversity dissimilarity of feedback under six cases.

the intermediate and later stages of coupled exploration, the divergence in inter-team feedback is reduced. The more frequent the perturbations occur between teams, the greater the divergence in the feedback provided by other teams. We have also observed that in cases where the team's ability to select the appropriate solution is weak, frequent perturbations not only impede the collaborative exploration process but also result in a lack of consensus among teams and even more conflicting proposals. This exacerbates the challenge faced by actors in making well-informed decisions based on feedback.

Before a genuine shared understanding can emerge, it is crucial for teams to establish consensus on innovative solutions as a basis for subsequent collaborative exploration and actionable measures. Indeed, during the initial stages of interaction, teams may achieve a transient consensus; however, divergent perspectives gradually emerge as they delve deeper into their exploration. After an initial consensus has been reached, it is also possible to accommodate divergent perspectives within the various teams (Harvey and Mueller, 2021). These diverse perspectives present potential for innovation in the intermediate and advanced stages. Our simulation results demonstrate that inter-team low frequency perturbations can effectively foster consensus, even in the presence of divergent opinions within each team. However, frequent perturbations in the early stages will reveal or highlight the divergent views among the different teams. In this scenario, these teams may hastily arrive at a superficial agreement by opting for an option without fully exploring potential solutions.

Inconsistent feedback from other teams poses challenges for the recipient, making it difficult to make judgments and leading to collective confusion (Knudsen and Srikanth, 2014). The impact of actions may not be immediately evident in the current period, and the causal relationship between decisions and outcomes might only become discernible after several subsequent stages (Denrell et al., 2004, Fang and Levinthal, 2009). Agents are unable to discern whether the positive or negative feedback stems from their own decisions or various external factors. Inconsistent feedback and suggestions from other teams exacerbate the complexity of their judgment, thereby augmenting the potential for misguidance and increasing the likelihood of both types of errors. The incorrect choice is subsequently disseminated to other relevant teams, thereby initiating a chain reaction of misdirection that mutually impacts each other. Making hasty decisions without consistent feedback may temporarily avoid disputes and conflicts, but subsequent actions based on a flawed set of actions will significantly deviate the exploration from the correct trajectory.

5. Sensitivity analysis

In the preceding section of the analysis, the number of subsystems, the number of teams, and the size of each team were kept constant. However, in practice, the complexity of R&D objects faced by each enterprise differs, and the sizes of R&D teams also vary significantly. Therefore, we conducted a sensitivity analysis for the parameters in the model, as shown in Table 2. For each parameter modification, we conducted 300 simulations. Table 2 lists the mean values and ranges of coupled exploration performance under different parameters.

When the parameter *w* changes from 25 to 10, the number of members per team in the system decreases from 25 to 10. In this case, the performance of coupled exploration will seriously decline. If the number of members per team is increased to 50, the coupled exploration performance improves to some extent, but the improvement is not significant. If the team size is too large, it will be difficult to quickly form a consensus in the face of perturbations from other teams. It can be seen that the continuous increase in the size of a single team does not bring obvious benefits but will cause the enterprise to incur additional costs. When parameter m decreases from 25 to 10, both the number of subsystems and the number of teams participating in joint exploration are reduced to 10, thereby improving the performance of coupled exploration. The coupled exploration performance metric presented here is a standardized indicator that quantifies the extent of performance attainment.

If m is increased to 40, the computer simulation slows down significantly because there are a total of 40*40 coupling relationships in the system, making multi-team coupling exploration very challenging. In this case, an excessive reduction in the size of each team will seriously hinder the progress of coupled exploration.

6. Conclusion and discussion

The teams engaged in the collaborative exploration will exchange feedback upon receiving parameters from each other, encompassing clarification, inquiries, suggestions for enhancement, and even critique of the existing solution. The team must make adjustments to the parameters in response to these recommendations that cannot be disregarded, resulting in a deviation of the technical solution from its original trajectory. This process is referred to as perturbation. Upon completion of the brainstorming session, establishment of development goals, and definition of the division of labor by all teams, they proceed to the phase of coupled exploration. The coupled exploration phase has the potential to foster significant innovations, but it also carries the risk of establishing a flawed system. The impact of inter-team perturbations on the results of coupling exploration has not been considered in previous studies. In this study, we employ a multi-agent simulation-based approach to analyze the initial problem.

The findings indicate that both excessively high and excessively low perturbation frequencies have detrimental effects on the coupling exploration process, addressing Questions 1 and 2 raised at the beginning of the paper. The performance of coupled exploration can be highly sensitive to the rate at which the optimal solution becomes established within a team in the presence of frequent perturbation among teams. Frequent perturbations can expedite the search for the global optimal solution among all teams, provided that better solutions can be quickly replicated within the team and consensus can be promptly reached. Revisions to previous choices are effectively minimized in subsequent stages by this model. If consensus formation is slow within each team, frequent perturbations from other teams can be misleading and hinder the collaborative exploration process. The frequent perturbations in the early stage not only impact the immediate performance of exploration but also have a lasting effect on subsequent exploratory

Journal of Engineering and Technology Management 77 (2025) 101899

Table 2 Sensitivity analysis.

m,n	w	frequency of perturbation						remarks
		Case1	Case2	Case3	Case4	Case5	Case6	
25	10	(29.59,32.18)	(52.21,59.18)	(42.79,46.24)	(54.85,60.50)	(54.63,60.93)	(42.36,47.94)	range
	25	54.31	66.78	60.88	71.66	73.11	59.96	average
	50	(56.01,60.46)	(67.47,73.34)	(64.79,67.99)	(75.25,81.35)	(77.28,83.22)	(66.19,68.99)	range
10	10	(38.8,56.80)	(83.89,94.3)	(42.40,53.21)	(87.3,92.81)	(67.42,82.32)	(45.93,65.90)	range
	25	69.43	91.83	71.96	92.68	93.91	77.34	average
	50	(82.01,90.99)	(91,01,96.41)	(76.64,91.02)	(93.66,99.28)	(89.43,98.77)	(82.15,91.08)	range
40	10	(20.03,22.87)	(46.83,53.87)	(33.83,37.90)	(46.12,49.74)	(42.90,49.71)	(36.2,41.72)	range
	25	41.86	59.96	45.46	57.64	56.87	47.02	average
	50	(49.75,52.44)	(57.03,61.97)	(50.54,56.48)	(57.02,63.15)	(58.12,64.06)	(49.92,54.89)	range

behavior. The results of our study indicate that frequent early perturbations significantly enhance the sensitivity of coupled exploration behavior to variations in learning ability within the team. In the later stages, frequent perturbations can result in rapid growth in exploration performance, contingent upon a team's robust internal learning capacity. If the team lacks the capacity to effectively and promptly discern appropriate choices, frequent perturbations can exacerbate their mutual misguidance. The exploration model coupled with frequent perturbations in both early and late stages may not necessarily facilitate the identification of the globally optimal choice.

This study prompts us to reconsider the communication mechanism between teams in coupled exploration. The dual role of feedback mechanisms needs to be reexamined. During the course of exploration activities, frequent communication among teams is essential for the purpose of resolving common confusion, enhancing existing solutions, and fostering novel ideas (Joseph and Gaba, 2020, Puranam et al. 2012, Knudsen and Srikanth, 2014, Puranam and Swamy, 2016, Perry-Smith and Mannucci, 2017, Mannucci and Perry-Smith, 2022, Toivonen et al. 2023). However, it has been demonstrated by other studies that feedback containing biased and negative suggestions can exacerbate conflicts, compel teams to abandon more valuable solutions, and ultimately result in suboptimal outcomes (Blair and Mumford, 2007, Mainemelis, 2010, Girotra et al. 2010, Rahman and Barley, 2017, Grimes, 2018, Fisher et al. 2018, Kim and Kim, 2020; Van der Voet,2023). The inundation of questions and suggestions also leads to information overload, thereby impeding actors' ability to make well-informed and rational judgments (Baird et al. 2000, O'Reilly, 1980, Piezunka and Dahlander, 2015, Harrison and Rouse, 2015). Our simulation experiment also confirms the aforementioned issue, indicating that while perturbations may enhance equilibrium performance, they can also hinder the process of coupling exploration. We discovered that the impact of perturbations is twofold, contingent upon their frequency and timing. Different stages of coupling exploration require teams to employ varying frequencies of perturbations.

The collaborative exploration activities of multidisciplinary teams necessitate the establishment of a cohesive perspective on the same problem within the framework of diverse and innovative ideas (Larey and Paulus, 1999, Putman and Paulus, 2009, Paletz and Schunn, 2010). The objective of coupling exploration is to facilitate cross-functional teams in overcoming cognitive differences and ultimately reaching a more accurate and innovative consensus (Salazar et al. 2012, Knudsen and Srikanth, 2014, Martins and Sohn, 2022). The presence of conflicting opinions among teams is strongly correlated with a high frequency of perturbations. Furthermore, the slow process of consensus formation within teams exacerbates the inconsistency in feedback information across teams. If there are frequent perturbations during the initial phases of coupling exploration, it is likely that teams will hold divergent perspectives on the feedback information; whereas if these perturbations occur during the intermediate and advanced stages of coupled exploration, feedback across teams tends to exhibit greater consistency. The presence of inconsistent feedback from other teams poses a challenge for actors in making accurate judgments, thereby increasing the likelihood of both type I and type II errors.

This study provides practical guidance for the research and development of enterprises. The impact of external perturbations on creativity varies at different stages of product development. Actors tend to exhibit a preference for adhering to established, easily predictable, and validated concepts while showing an inclination to dismiss novel and seemingly radical ideas during initial internal deliberations (Mueller et al. 2012, Piezunka and Dahlander, 2015, Criscuolo et al. 2017, Harvey and Mueller, 2021). If teams take longer to reach a consensus or invest more time and effort in integrating diverse ideas and opinions, they are more likely to sustain the vitality of new ideas (Paletz and Schunn, 2010, Harvey and Mueller, 2021). Mutual feedback plays a crucial role in consensus

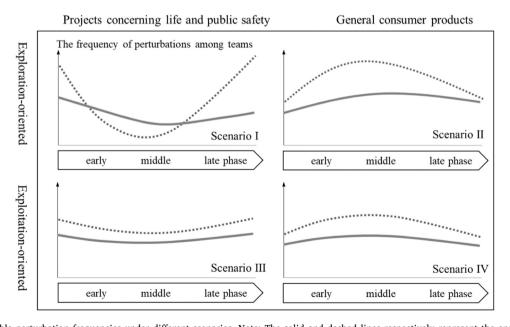


Fig. 7. Suitable perturbation frequencies under different scenarios, Note: The solid and dashed lines respectively represent the appropriate frequencies of mutual perturbation among multiple teams when the speed of screening excellent options and reaching consensus is slow and fast.

formation; however, the precise conditions under which consensus is achieved to enhance coupled exploration remain elusive. The provision of negative or critical feedback following the completion of innovative work may serve to safeguard exploratory behavior. The communication patterns and frequency we suggest will both facilitate the accumulation of experience in innovative work and prevent the premature stifling of creativity. The advantages of slow learning are widely recognized in the context of coupled search (Denrell and March, 2001, March, 2006, Knudsen and Levinthal, 2007, Fang et al. 2010, Knudsen and Srikanth, 2014). The findings of this study contradict this perspective and contribute additional insights to it. The sluggish progress of individual teams in concurrent engineering can impede the overall project development. What each team needs to do is determine the key parameters accurately and efficiently. Frequent perturbations also indicate actors' inclination towards exploring at a faster pace, but the frequency of these perturbations should align with the exploration capabilities of other teams and the learning speed within the team. The chaotic state will be exacerbated when the coupling exploration encounters a bottleneck, and frequent perturbations will further intensify it. When the team's learning ability is weak and it becomes difficult to quickly identify the correct choices, temporarily reducing the frequency of perturbations and allocating more time for exploration should be considered. The purpose of this is to prevent teams from settling for suboptimal alternatives in their pursuit of superficial uniformity.

Based on the findings of this study, Fig. 7 serves as a comprehensive summary that encapsulates the key insights. The first scenario involves the research and development of projects related to life safety (such as aerospace, military industries, nuclear facilities, etc.) and oriented towards exploration. If the learning capabilities of each research team are strong, they can quickly reach a consensus and determine the best option. Then, in the early stage of project development, each team can frequently propose various suggestions to reject schemes that seem correct but ultimately contain dangerous factors and hidden risks; in the later stage, a large amount of data integration work is required. At this time, frequent mutual feedback can improve the reliability and safety of the system. Even if each research team has difficulty reaching a consensus quickly, in the initial stage, questions need to be frequently raised and feedback from other teams is required to ensure that the exploration directions of all teams are consistent with the overall goal. The second scenario involves R&D projects for general consumer-oriented products that are exploration-driven. In the early stage, it is necessary to leave more room for independent exploration for each team and retain radical and diverse ideas, avoiding the negation of radical and innovative viewpoints by negative feedback. At this time, the mutual perturbation among different teams should be moderately reduced to prevent premature convergence. In the middle stage, although a large amount of mutual disturbance may slow down the progress of product RandD, the opinions and feedback exchanged among teams can promote the generation of innovative ideas and product improvement, which avoids extensive modifications in the later stage.

The third scenario involves projects that are life safety-related and oriented towards exploitation. Due to the availability of data and parameters from similar projects, the frequency of feedback among teams can be more stable. As major differences have already been resolved in other similar projects, the current extensive questioning and feedback are merely aimed at fine-tuning and improving the plan to ensure more efficient collaboration among subsystems and to guarantee that the entire system has higher reliability and security. The fourth scenario involves R&D projects for general consumer products that are oriented towards exploitation. In this case, a moderate level of disturbance in the early stage can ensure the consistency of goals among various teams. Compared with scenario 2, there is no need for excessive mutual disturbance in the middle stage. Especially when it is difficult for each team to deeply explore and reach a consensus, moderately reducing the disturbance can help avoid differences of opinion and repeated modifications to the plan, thereby accelerating the progress of the R&D work.

The noteworthy point is that we have also implemented novel research methodologies. The coupling between subsystems is described based on the social learning model (March, 1991, Miller et al. 2006, Kane and Alavi, 2007, Fang et al. 2010, Posen et al. 2013, Knudsen and Srikanth, 2014, Miller and Lin, 2015, Kim and Anand, 2018, Mi et al. 2023), by constructing the interrelation among tuples. Compared to the traditional NK model, the proposed method enhances the robustness of the model and mitigates the impact of initial data randomness, thereby yielding more consistent results across multiple simulations. We anticipate further refinement of the model in relation to other pertinent research inquiries. A limitation of this study is that our research primarily focuses on the coupled exploration phase, under the assumption that the team objectives and the subsystems responsible for each team member are fully defined before this stage. We assume that the size of each team is fixed and do not take into account the characteristics of virtual teams or the turnover of employees between teams. In addition, we did not include an analysis of multi-level organizations or multi-team joint R&D models with centralized coordination mechanisms. Future research could explore the imbalance in information transfer between teams and the integration of knowledge across diverse teams.

CRediT authorship contribution statement

Mi Jie: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jiamin Dong:** Writing – review & editing, Supervision, Resources.

Acknowledgements

This work was supported by the Humanities and Social Sciences Youth Foundation, Ministry of Education (24YJCZH215), National Natural Science Foundation of China (71902130) and National Natural Science Foundation of China (72302236).

References

- Asplund, F., Björk, J., Magnusson, M., 2022. Knowing too much? On bias due to domain-specific knowledge in internal crowdsourcing for explorative ideas. RD Manag. 52 (4), 720–734.
- Ávila-Robinson, A., Sengoku, S., 2017. Multilevel exploration of the realities of interdisciplinary research centers for the management of knowledge integration. Technovation 62, 22-41.
- Baird, F., Moore, C.J., Jagodzinski, A.P., 2000. An ethnographic study of engineering design teams at Rolls-Royce Aerospace. Des. Stud. 21 (4), 333-355.
- Baumann, O., Siggelkow, N., 2013. Dealing with complexity: integrated vs. chunky search processes. Organ. Sci. 24 (1), 116-132.
- Baumann, O., Schmidt, J., Stieglitz, N., 2019. Effective search in rugged performance landscapes: a review and outlook. J. Manag. 45 (1), 285-318.
- Ben-Menahem, S.M., Von Krogh, G., Erden, Z., Schneider, A., 2016. Coordinating knowledge creation in multidisciplinary teams: evidence from early-stage drug discovery. Acad. Manag. J. 59 (4), 1308–1338.
- Bergenholtz, C., Vuculescu, O., Amidi, A., 2023. Microfoundations of adaptive search in complex tasks: the role of cognitive abilities and styles. Organ. Sci. 34 (6), 2043–2063.
- Bernstein, E., Shore, J., Lazer, D., 2018. How intermittent breaks in interaction improve collective intelligence. Proc. Natl. Acad. Sci. 115 (35), 8734-8739.
- Billinger, S., Srikanth, K., Stieglitz, N., Schumacher, T.R., 2021. Exploration and exploitation in complex search tasks: how feedback influences whether and where human agents search. Strateg. Manag. J. 42 (2), 361–385.
- Blair, C.S., Mumford, M.D., 2007. Errors in idea evaluation: preference for the unoriginal? J. Creat. Behav. 41 (3), 197-222.
- Bruns, H.C., 2013. Working alone together: coordination in collaboration across domains of expertise. Acad. Manag. J. 56 (1), 62-83.
- Burnell, D., Stevenson, R., Fisher, G., 2023. Early-stage business model experimentation and pivoting. J. Bus. Ventur. 38 (4), 106314.
- Cardinal, L.B., Turner, S.F., Fern, M.J., Burton, R.M., 2011. Organizing for product development across technological environments: performance trade-offs and priorities. Organ. Sci. 22 (4), 1000–1025.
- Chen, Q., Magnusson, M., Björk, J., 2020. Collective firm-internal online idea development: exploring the impact of feedback timeliness and knowledge overlap. Eur. J. Innov. Manag. 23 (1), 13–39.
- Clement, J., 2023. Missing the forest for the trees: modular search and systemic inertia as a response to environmental change. Adm. Sci. Q. 68 (1), 186-227.
- Criscuolo, P., Dahlander, L., Grohsjean, T., Salter, A., 2017. Evaluating novelty: the role of panels in the selection of R&D projects. Acad. Manag. J. 60 (2), 433–460. Cronin, M.A., Weingart, L.R., 2007. Representational gaps, information processing, and conflict in functionally diverse teams. Acad. Manag. Rev. 32 (3), 761–773. De Dreu, C.K., 2003. Time pressure and closing of the mind in negotiation. Organ. Behav. Hum. Decis. Process. 91 (2), 280–295.
- De Stobbeleir, K.E., Ashford, S.J., Buyens, D., 2011. Self-regulation of creativity at work: the role of feedback-seeking behavior in creative performance. Acad. Manag. J. 54 (4), 811–831.
- Denrell, J., March, J.G., 2001. Adaptation as information restriction: the hot stove effect. Organ. Sci. 12 (5), 523-538.
- Denrell, J., Fang, C., Levinthal, D.A., 2004. From T-mazes to labyrinths: learning from model-based feedback. Manag. Sci. 50 (10), 1366-1378.
- Edmondson, A.C., Nembhard, I.M., 2009. Product development and learning in project teams: the challenges are the benefits. J. Prod. Innov. Manag. 26 (2), 123–138.
- Fang, C., Levinthal, D., 2009. Near-term liability of exploitation: exploration and exploitation in multistage problems. Organ. Sci. 20 (3), 538-551.
- Fang, C., Lee, J., Schilling, M.A., 2010. Balancing exploration and exploitation through structural design: the isolation of subgroups and organizational learning. Organ. Sci. 21 (3), 625–642.
- Fisher, C.M., Pillemer, J., Amabile, T.M., 2018. Deep help in complex project work: guiding and path-clearing across difficult terrain. Acad. Manag. J. 61 (4), 1524–1553.
- Gavetti, G., Greve, H.R., Levinthal, D.A., Ocasio, W., 2012. The behavioral theory of the firm: assessment and prospects. Acad. Manag. Ann. 6 (1), 1-40.
- Ghosh, S., Wu, A., 2023. Iterative coordination and innovation: prioritizing value over novelty. Organ. Sci. 34 (6), 2182-2206.
- Girotra, K., Terwiesch, C., Ulrich, K.T., 2010. Idea generation and the quality of the best idea. Manag. Sci. 56 (4), 591-605.
- Golder, P.N., Shacham, R., Mitra, D., 2009. Findings—innovations' origins: when, by whom, and how are radical innovations developed? Mark. Sci. 28 (1), 166–179. Grimes, M.G., 2018. The pivot: how founders respond to feedback through idea and identity work. Acad. Manag. J. 61 (5), 1692–1717.
- Harrison, S.H., Rouse, E.D., 2015. An inductive study of feedback interactions over the course of creative projects. Acad. Manag. J. 58 (2), 375-404.
- Harvey, S., 2013. A different perspective: the multiple effects of deep level diversity on group creativity. J. Exp. Soc. Psychol. 49 (5), 822-832.
- Harvey, S., 2014. Creative synthesis: exploring the process of extraordinary group creativity. Acad. Manag. Rev. 39 (3), 324-343.
- Harvey, S., Kou, C.Y., 2013. Collective engagement in creative tasks: the role of evaluation in the creative process in groups. Adm. Sci. Q. 58 (3), 346-386.
- Harvey, S., Mueller, J.S., 2021. Staying alive: toward a diverging consensus model of overcoming a bias against novelty in groups. Organ. Sci. 32 (2), 293-314.
- Hauptman, O., Hirji, K.K., 1999. Managing integration and coordination in cross-functional teams: an international study of Concurrent Engineering product development. RD Manag. 29 (2), 179–192.
- Hoever, I.J., Zhou, J., Van Knippenberg, D., 2018. Different strokes for different teams: the contingent effects of positive and negative feedback on the creativity of informationally homogeneous and diverse teams. Acad. Manag. J. 61 (6), 2159–2181.
- Hu, S., Bettis, R.A., 2018. Multiple organization goals with feedback from shared technological task environments. Organ. Sci. 29 (5), 873–889.
- Jafari Songhori, M., Nasiry, J., 2020. Organizational structure, subsystem interaction pattern, and misalignments in complex NPD projects. Prod. Oper. Manag. 29 (1), 214–231
- Jafari Songhori, M., Tavana, M., Terano, T., 2020. Product development team formation: effects of organizational-and product-related factors. Comput. Math. Organ. Theory 26 (1), 88–122.
- Jehn, K.A., 1995. A multimethod examination of the benefits and detriments of intragroup conflict. Adm. Sci. Q. 256-282.
- Joseph, J., Gaba, V., 2020. Organizational structure, information processing, and decision-making: a retrospective and road map for research. Acad. Manag. Ann. 14 (1), 267–302.
- Kane, G.C., Alavi, M., 2007. Information technology and organizational learning: an investigation of exploration and exploitation processes. Organ. Sci. 18 (5), 796–812.
- Kim, S., Anand, J., 2018. Knowledge complexity and the performance of inter-unit knowledge replication structures. Strateg. Manag. J. 39 (7), 1959-1989.
- Kim, Y.J., Kim, J., 2020. Does negative feedback benefit (or harm) recipient creativity? The role of the direction of feedback flow. Acad. Manag. J. 63 (2), 584–612. Knudsen, T., Levinthal, D.A., 2007. Two faces of search: alternative generation and alternative evaluation. Organ. Sci. 18 (1), 39–54.
- Knudsen, T., Srikanth, K., 2014. Coordinated exploration: organizing joint search by multiple specialists to overcome mutual confusion and joint myopia. Adm. Sci. Q. 59 (3), 409–441.
- Larey, T.S., Paulus, P.B., 1999. Group preference and convergent tendencies in small groups: a content analysis of group brainstorming performance. Creat. Res. J. 12 (3), 175–184.
- Levinthal, D.A., 1997. Adaptation on rugged landscapes. Manag. Sci. 43 (7), 934-950.
- Majchrzak, A., More, P.H., Faraj, S., 2012. Transcending knowledge differences in cross-functional teams. Organ. Sci. 23 (4), 951–970.
- Mannucci, P.V., Perry-Smith, J.E., 2022. "Who are you going to call?" Network activation in creative idea generation and elaboration. Acad. Manag. J. 65 (4), 1192–1217.
- Mainemelis, Charalampos, 2010. "Stealing fire: creative deviance in the evolution of new ideas. Acad. Manag. Rev. 35.4, 558-578.
- March, J.G., 1991. Exploration and exploitation in organizational learning. Organ. Sci. 2 (1), 71-87.
- March, J.G., 2006. Rationality, foolishness, and adaptive intelligence. Strateg. Manag. J. 27 (3), 201–214.
- Martins, L.L., Sohn, W., 2022. How does diversity affect team cognitive processes? Understanding the cognitive pathways underlying the diversity dividend in teams. Acad. Manag. Ann. 16 (1), 134–178.
- Mertens, S., Schollaert, E., Anseel, F., 2021. How much feedback do employees need? A field study of absolute feedback frequency reports and performance. Int. J. Sel. Assess. 29 (3-4), 326–335.

Mi, J., Xie, Z., Lv, S., 2023. Star-studded or equalitarianism: how does the distribution of creative stars affect exploration–exploitation balance? Comput. Math. Organ. Theory 29 (2), 336–362.

Mi, J., Zhao, X., Lv, S., 2024. Exploration or exploitation orientation, subgroup structure and organizational knowledge creation. Innovation. https://doi.org/10.1080/14479338.2024.2302114.

Miller, K.D., Lin, S.J., 2015. Analogical reasoning for diagnosing strategic issues in dynamic and complex environments. Strateg. Manag. J. 36 (13), 2000–2020. Miller, K.D., Zhao, M., Calantone, R.J., 2006. Adding interpersonal learning and tacit knowledge to March's exploration-exploitation model. Acad. Manag. J. 49 (4), 709–722

Mueller, J.S., Melwani, S., Goncalo, J.A., 2012. The bias against creativity: why people desire but reject creative ideas. Psychol. Sci. 23 (1), 13-17.

Olsen, A.Ø., Sofka, W., Grimpe, C., 2016. Coordinated exploration for grand challenges: the role of advocacy groups in search consortia. Acad. Manag. J. 59 (6), 2232–2255

O'Reilly III, C.A., 1980. Individuals and information overload in organizations: is more necessarily better? Acad. manag. j. 23 (4), 684-696.

O'Reilly, C., Binns, A.J., 2019. The three stages of disruptive innovation: idea generation, incubation, and scaling. Calif. Manag. Rev. 61 (3), 49-71.

Paletz, S.B., Schunn, C.D., 2010. A social-cognitive framework of multidisciplinary team innovation. Top. Cogn. Sci. 2 (1), 73-95.

Pateli, A., Lioukas, S., 2019. How functional involvement affects the transformation of external knowledge into innovation outcomes. RD Manag. 49 (2), 224–238. Park, S., Piezunka, H., Dahlander, L., 2024. Coevolutionary lock-in in external search. Acad. Manag. J. 67 (1), 262–288.

Perry-Smith, J.E., Mannucci, P.V., 2017. From creativity to innovation: the social network drivers of the four phases of the idea journey. Acad. Manag. Rev. 42 (1), 53–79.

Piezunka, H., Dahlander, L., 2015. Distant search, narrow attention: how crowding alters organizations' filtering of suggestions in crowdsourcing. Acad. Manag. J. 58 (3), 856–880.

Posen, H.E., Lee, J., Yi, S., 2013. The power of imperfect imitation. Strateg. Manag. J. 34 (2), 149–164.

Puranam, P., Swamy, M., 2016. How initial representations shape coupled learning processes. Organ. Sci. 27 (2), 323-335.

Puranam, P., Raveendran, M., Knudsen, T., 2012. Organization design: the epistemic interdependence perspective. Acad. Manag. Rev. 37 (3), 419-440.

Putman, V.L., Paulus, P.B., 2009. Brainstorming, brainstorming rules and decision making. J. Creat. Behav. 43 (1), 29-40.

Rahman, H.A., Barley, S.R., 2017. Situated redesign in creative occupations-An ethnography of architects. Acad. Manag. Discov. 3 (4), 404-424.

Reid, S.E., De Brentani, U., 2004. The fuzzy front end of new product development for discontinuous innovations: a theoretical model. J. Prod. Innov. Manag. 21 (3), 170–184

Rogers, E.M., Adhikarya, R., 1979. Diffusion of innovations: an up-to-date review and commentary. Ann. Int. Commun. Assoc. 3 (1), 67-81.

Rubenson, D.L., Runco, M.A., 1992. The psychoeconomic approach to creativity. N. Ideas Psychol. 10 (2), 131–147.

Salazar, M.R., Lant, T.K., Fiore, S.M., Salas, E., 2012. Facilitating innovation in diverse science teams through integrative capacity. Small Group Res. 43 (5), 527–558. Siggelkow, N., Rivkin, J.W., 2009. Hiding the evidence of valid theories: how coupled search processes obscure performance differences among organizations. Adm. Sci. O. 54, 602–634.

Song, X.M., Thieme, R.J., Xie, J., 1998. The impact of cross-functional joint involvement across product development stages: an exploratory study. J. Prod. Innov. Manag. 15 (4), 289–303.

Srikanth, K., Ungureanu, T., 2025. Organizational adaptation in dynamic environments: disentangling the effects of how much to explore versus where to explore. Strateg. Manag. J. 46 (1), 19–48.

Ter Wal, A.L., Criscuolo, P., Salter, A., 2023. Inside-out, outside-in, or all-in-one? The role of network sequencing in the elaboration of ideas. Acad. Manag. J. 66 (2), 432–461.

Toivonen, T., Idoko, O., Jha, H.K., Harvey, S., 2023. Creative jolts: exploring how entrepreneurs let go of ideas during creative revision. Acad. Manag. J. 66 (3), 829–858.

Tushman, M.L., Nadler, D.A., 1978. Information processing as an integrating concept in organizational design. Acad. Manag. Rev. 3 (3), 613-624.

Van der Voet, J., 2023. Search in response to negative performance feedback: problem-definition and solution-generation. J. Public Adm. Res. Theory 33 (1), 43–62. Van de Ven, A.H., 1986. Central problems in the management of innovation. Manag. Sci. 32 (5), 590–607.

Van Werven, R., Cornelissen, J., Bouwmeester, O., 2023. The relational dimension of feedback interactions: a study of early feedback meetings between entrepreneurs and potential mentors. Br. J. Manag. 34 (2), 873–897.

Yuan, F., Zhou, J., 2008. Differential effects of expected external evaluation on different parts of the creative idea production process and on final product creativity. Creat. Res. J. 20 (4), 391–403.

Jie Mi is an associate professor in College of Economics and Management, Taiyuan University of Technology. He has received his PhD from Nankai University, China. His research interests include evolution of organizational routine, multi-agent simulation and social network. His recent research explores the effect of the network structure on performance in terms of exploration and exploitation, and the evolution of the organization's internal network structure.

Jiamin Dong is an assistant professor at Central South University, Changsha, China. Her research interests cover knowledge management, organizational learning, strategic management, and agent-based simulation. Her work has been published in The Leadership Quarterly, European Management Review, and Systems Engineering—Theory & Practice and so on.