

Methodological Approaches to Studying Group Behavior: From Human Interaction to Agent-Based Models

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Abstract

Understanding group behavior demands a careful balance between ecological validity and experimental control, yet progress has often been constrained by methodological limitations. Despite these challenges, researchers have developed rigorous paradigms beyond traditional economic games—for example, collective foraging—particularly by leveraging new technologies such as virtual reality and large language models. To make sense of these advancements, this article proposes a conceptual and methodological framework for studying group behavior across three complementary approaches: (1) human–human interaction with controlled agents, (2) human–agent interaction with algorithm-driven behavior, and (3) agent–agent interaction through simulation. Leveraging advances in digital platforms, computational modeling, and large language model-driven agents, these approaches enable experimental probing of how local interactions give rise to group-level patterns. Each approach presents distinct trade-offs in realism, control, and scalability, and their integration allows for triangulation of findings and deeper theoretical insight. We advocate for integrating these approaches, where humans and intelligent agents interact within controlled yet realistic scenarios, designing algorithmic agents with more humanlike parameters, and combining them with advanced data collection techniques. This framework supports a richer understanding of human group behavior in an increasingly hybrid human–machine social landscape.

Keywords

group behavior, human–human interaction, human–agent interaction, agent–agent interaction

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Human beings are not isolated; they naturally form groups—whether to achieve a common goal or simply to wait together—interacting with and influencing one another in the process. These interactions give rise to group behaviors that are not merely the sum of individual psychological processes. Instead, group behavior encompasses collective phenomena that emerge from dynamic interactions among group members (Warren et al., 2024). A typical example is the spontaneous movement patterns of pedestrians in crowded spaces (Goldstone & Roberts, 2006). Crucially, such emergent patterns at the group level arise from local interactions guided by individuals' cognitive abilities, rather than from any centralized coordination (Turcotte & Rundle, 2002). Establishing a clear connection between the micro-level processes of individual cognition and the macro-level patterns of collective behavior has long been a central challenge in the study of group behavior, yet progress has often been constrained by methodological limitations (Vallacher et al., 2017). Despite these challenges,

researchers have developed rigorous paradigms beyond traditional economic games—for example, collective foraging (Wu et al., 2025)—particularly by leveraging new technologies such as virtual reality (VR) (Pan & Hamilton, 2018) and large language models (LLMs) (Gao et al., 2024). To make sense of these advancements, it is crucial to systematically organize them within a unified framework. This paper advances a research perspective by outlining a conceptual and methodological framework for

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studying group behavior across three complementary approaches: human–human interaction with controlled agents, human–agent interaction with algorithm-driven action, and agent–agent interaction through simulation.

Experimental Challenges in Studying Group Behavior

Naturalistic observations are extensively utilized in the study of group behaviors due to their high ecological validity and the challenges of running controlled experiments (Sieben & Postmes, 2025). By observing individuals within their natural environments without interference, researchers can gain authentic insights into spontaneous behaviors and social interactions. This approach is particularly effective for understanding complex group dynamics, such as communication patterns, crowd dynamics. To explore the contributions of individual cognition to group patterns, researchers can measure parameters at both micro (individual) and macro (group) levels, and use statistical methods like hierarchical linear modeling (HLM) are employed to analyze the relationships between these levels (Urizar et al., 2016). However, naturalistic observation methods present challenges, including limited control over variables and potential observer bias. It is particularly difficult to establish causal explanations from individual cognition to collective behaviors in such settings (Angrosino & Rosenberg, 2011). Therefore, while naturalistic observations offer rich, contextual insights into group behaviors, it is important to develop experimental frameworks that can complement these observations. Such frameworks would aim to balance ecological validity with the need for experimental control, facilitating a more comprehensive understanding of the causal relationships underlying group dynamics.

Nevertheless, the study of group behavior still presents several challenges that complicate experimental control, the establishment of causal relationships, and ethical issues. First, group behavior is inherently complex due to the dynamic interactions among individuals, which can lead to emergent behaviors that are not predictable from individual actions alone. This complexity makes it difficult to isolate specific causal factors, requiring a nuanced understanding of how group structures, norms, and individual behaviors shape collective outcomes (Vallacher & Nowak, 1997). For example, subtle differences in group composition or communication patterns can lead to significantly different group dynamics, influenced by factors such as personality, cognitive abilities, or social preferences (Lehmann-Willenbrock et al., 2017). Second, individual variability adds further complexity, as differences in traits like leadership tendencies or conformity can significantly impact group processes. Some individuals may naturally assume leadership roles, while others may align with group consensus, making it challenging to generalize findings or isolate the influence of specific

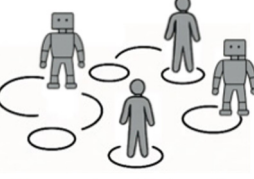
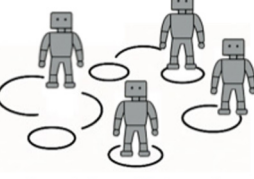
individuals (Emery et al., 2013). Third, establishing causality in group behavior is difficult due to the interplay between individual cognition and collective dynamics (Arrow et al., 2000). Experimental designs that focus solely on individual actions or group outcomes may fail to capture the bidirectional influence between these levels. Finally, ethical concerns arise when manipulating group behavior in controlled settings, as experiments involving deception, stress, or emotional manipulation (e.g., inducing conflict or conformity pressure) can affect participants' well-being (Zimbardo, 2017). For instance, studies on group pressure may lead participants to feel coerced, raising concerns about autonomy and psychological distress.

Three Conceptual Approaches to Studying Group Behavior

To address the challenges in studying group behavior, experimental paradigms based on economic games, such as the Public Goods Game, Trust Game, and Group Voting, have been widely used (Bose et al., 2017; Pisor et al., 2020). These games simplify complex social interactions into structured scenarios with clear rules and incentives, enabling researchers to observe how individuals and groups make decisions under controlled conditions. They offer insights into decision-making in the presence of others, cooperation versus competition, and the emergence of group dynamics. However, the reliance on economic games—while effective—often reduces group behavior to decision outcomes (e.g., cooperation vs. defection), neglecting important process-level dynamics such as norm emergence and movement-based collective action. In reality, group behavior is more than just decision-making; it involves a wide range of actions, interactions, and dynamics within social contexts (Lehmann-Willenbrock et al., 2017). As a result, researchers are developing a broader set of behavioral experimental paradigms that aim to capture the full spectrum of group behavior, including collective foraging and agent-based simulations (ABM). With recent advancements in technology, these paradigms are expanding the research landscape by incorporating interactions with robots, virtual agents, and other new technologies, moving beyond traditional economic games (Pan & Hamilton, 2018; Rahwan et al., 2019). These paradigms provide insights into dynamic, interactive processes within groups, capturing emergent properties from local interactions and revealing the cognitive and social mechanisms underlying group-level outcomes. By doing so, we can gain a deeper and more nuanced understanding of how individuals behave within groups and how collective patterns emerge.

These advancements encompass diverse designs and technologies, underscoring the need for systematic organization within a unified framework. This paper proposes a conceptual and methodological framework for studying

Table 1. Three Approaches to Studying Group Behavior.

Approach	Characteristic	Example
 Human-Human Interaction Participants control agents that interact according to fixed protocols	Control: Provides moderate control over the behavior of agents through human input but is limited by the need for human decision-making. Realism: Offers high realism, as the human-controlled agents interact in a dynamic, socially rich environment. Scalability: Limited scalability due to the need for human participation and coordination in controlled settings.	Ten individuals each control an avatar navigating a virtual fire escape scenario, with movements directed via keyboard input.
 Human-Agent Interaction Human participants interact with preprogrammed agents	Control: Offers high control over agent behavior through algorithmic rules, allowing for precise experimental manipulation. Realism: Achieves moderate realism, as the agents simulate human-like behaviors, but they may lack the depth of real human social dynamics. Scalability: Highly scalable, as multiple agents can be tested simultaneously in varied environments without the need for direct human interaction.	Within a virtual fire escape scenario, three individuals each control an avatar using keyboards, while the behaviors of seven peer avatars are algorithmically controlled.
 Agent-Agent Interaction Simulated agents follow rules to model social phenomena	Control: Provides the highest control, as agents' behaviors are entirely governed by pre-defined algorithms and rules. Realism: Limited realism, as agents follow specific, scripted rules that may not fully capture the complexity of human behavior. Scalability: Very scalable, allowing for the simulation of large groups or complex scenarios over extended periods with minimal resource constraints.	In a virtual fire escape scenario, the behaviors of ten agents are programmed with humanlike algorithms

group behavior across three complementary approaches, ranging from partially controlled human-human interactions to simulations with fully autonomous agents: human-human interaction with controlled agents, human-agent interaction with algorithm-driven actions, and agent-agent interaction through simulation (see Table 1). This framework does not aim to exclude traditional paradigms, such as economic games, but rather advocates for considering them alongside newly developed paradigms, such as collective forging, within a comprehensive approach to studying group behavior.

Human–Human Interaction with Controlled Agents

Understanding group behavior often begins with controlled studies in which real human participants interact under experimentally designed conditions. One promising yet underutilized approach in this domain is Human–Human Interaction with Human-Controlled Agents. Drawing

inspiration from the architecture of online multiplayer gaming environments, this approach enables the construction of real-time, interactive platforms where multiple participants control avatars or agents within a shared digital or virtual space (Kyrilitsias & Michael-Grigoriou, 2022; Molyneux et al., 2015; Wu et al., 2025). These agents engage in a variety of coordinated or competitive behaviors—such as following, evading, navigating obstacles, or engaging in simulated conflict—thereby simulating complex social environments that mirror real-world group dynamics.

In this setup, participants may be tasked with interacting alongside or against a group of “avatars”—human-controlled agents who follow predetermined behavioral scripts or protocols. For example, in a simulated fire-escape scenario, each participant sat in front of a computer and viewed the virtual environment from a first-person perspective, which included other participants represented as avatars. Using input devices such as a keyboard and mouse, participants could freely navigate the environment. This

setup allows researchers to observe how individuals adapt to or conform with the majority's escape choices. Moussaïd et al. (2016) employed such a platform to investigate crowd behavior in high-risk evacuation situations involving real human participants. In fact, experiments based on economic games can also be considered part of this approach. Although no explicit avatars are present in these games, participants make decisions within predefined rule structures and payoff settings, effectively functioning as controlled agents (Fehr & Gächter, 2002; Rand et al., 2011). This approach of human-human interaction with human-controlled agents allows researchers to explore how an individual's cognition, perception, and decision-making are influenced by, adapt to, and in turn shape the surrounding group behavior. It opens the door to questions such as: How do individuals conform to or diverge from observed group norms? What types of social cues are most influential in shifting behavior? How do moment-to-moment micro-interactions give rise to emergent group-level phenomena?

Unlike traditional confederate-based paradigms—typically conducted in face-to-face laboratory settings, such as Asch's conformity experiments—human-controlled agents are usually implemented in digital platforms or virtual environments. This digital format offers key advantages: interactions can be precisely timed, spatially constrained, and manipulated in context-specific ways, all while maintaining the illusion of natural social presence. Each "avatar" can be remotely directed to display specific behaviors—such as searching for rewards—allowing researchers to examine how subtle cues affect the target participant. For example, Deffner et al. (2024) conducted a naturalistic immersive-reality experiment in which groups of participants searched for rewards across different environments. By manipulating resource distribution (concentrated vs. distributed) and incentive structure (group vs. individual rewards), they found that group-level incentives reduced individuals' responsiveness to social information and encouraged greater behavioral selectivity over time.

Critically, this approach enables causal inferences about how local interactions contribute to emergent group behavior, as specific behaviors can be systematically selected, controlled, and reproduced across trials. A compelling example of this approach is provided by Nalepka and colleagues (2017), who investigated multiagent coordination using a digital herding task. In this study, pairs of participants were tasked with corralling virtual sheep toward the center of a shared game field. Initially, most participant pairs adopted a complementary "search-and-recover" strategy, in which each person primarily managed sheep on their respective side of the field. However, over time, many pairs spontaneously transitioned to a more effective coordination pattern: a coupled oscillatory containment strategy, wherein both participants moved synchronously around the herd in a dynamic, wave-like motion. These findings demonstrated how simple local interaction rules—such as following the

nearest neighbor or avoiding collisions—could give rise to complex emergent patterns at the group level.

This approach has limited capacity to capture truly emergent dynamics, as the "group" consists of controlled agents. To address this, findings are often paired with sensor-based tracking of real group interactions to capture nuanced responses. Nonetheless, human-human interaction with human-controlled agents remains a flexible and powerful approach for studying group behavior under semi-naturalistic yet controlled conditions.

Human-Agent Interaction with Algorithm-Driven Action

To enable more precise manipulation of others' actions, an increasingly prominent approach involves real humans interacting with algorithm-driven agents. Unlike human-controlled avatars, these agents operate according to preprogrammed rules or machine learning models that simulate social behaviors. This allows for fine-tuned experimental control, particularly over micro-level actions that are often critical to social coordination (Cross & Ramsey, 2021; Jiang et al., 2025). By abstracting away human variability, algorithm-driven agents can be configured with key parameters to isolate and test specific components of social behavior. For example, in studies of social conformity using a virtual fire-escape scenario, a participant controls an avatar via keyboard to select an exit route, while the behaviors of two peer avatars are algorithmically controlled to either choose the same exit or a different one (Yin et al., 2024). This setup enables researchers to precisely manipulate the majority's behavior, define how the majority is formed, and systematically examine conformity effects.

A major strength of this approach is its capacity to deliver rigorous, repeatable interventions while preserving the interactive richness of human social interaction. These agents can be programmed to exhibit emotional expressions, follow social norms, or simulate common cognitive biases. For instance, Hertz et al. (2025) introduced a multiagent reinforcement learning (MARL) approach, which builds on modern artificial intelligence techniques, and provides new avenues to model complex social worlds, while preserving more of their characteristics, and allowing them to capture a variety of social phenomena. Participants may not always recognize the artificial nature of these agents—or, even when aware, still respond to them as if they were genuine social partners. This makes it possible to engage real psychological mechanisms in a highly controlled setting, bridging the gap between experimental precision and ecological relevance. Furthermore, as contemporary social groups increasingly include artificial agents alongside humans, this framework offers critical insights into the evolving dynamics of human-agent collectives and the

emerging principles of group behavior in mixed-agent environments.

This approach has been used to investigate how interactive behavior is shaped by subtle social cues (Gao et al., 2010), how societies acquire and sustain social norms (Köster et al., 2022), and how intergroup bias emerges and persists (Nafcha & Hertz, 2024), among others. For example, by populating a foraging environment with artificial agents that must learn to avoid poisonous berries—and introducing a taboo that punishes the consumption of harmless ones—researchers showed that normative behavior develops through a sequence of learned skills, with rule compliance building on prior enforcement by others (Köster et al., 2022). Using algorithmically controlled confederates, Yin et al. (2024) demonstrated that individuals are more likely to follow the majority's choice when selecting from available options than when forced to make a unanimous decision.

The advancement of virtual reality (VR) and robotics has greatly expanded the potential of this paradigm by enabling ecologically valid, scalable, and cost-effective experimentation (Vasser & Aru, 2020). VR, in particular, allows researchers to construct highly immersive and controllable environments that approximate real-world social contexts while preserving experimental precision (Pan & Hamilton, 2018). The use of humanlike avatars further enhances ecological validity by eliciting natural social responses from participants. Through dynamic, interactive scenes, VR makes it possible to examine complex group phenomena such as crowd movement, evacuation dynamics, coordination under uncertainty, and the diffusion of social norms. For example, Zhou et al. (2019) developed a social interaction field model using VR, revealing a front-back asymmetry in social interactions. Moreover, VR platforms can systematically manipulate spatial layouts, perceptual cues, or incentive structures, providing insights into how environmental design influences emergent group patterns. With the addition of wearable motion tracking and physiological monitoring, VR also allows for the simultaneous measurement of fine-grained behavioral and cognitive responses, enriching the analysis of micro-to-macro links in group behavior.

Robotics provides a complementary pathway by offering physical embodiments of agents that mimic humanlike actions in shared environments (Belpaeme et al., 2018). Robots can be programmed to perform consistent, repeatable behaviors, serving as scientific instruments rather than just social partners (Bärman et al., 2024). This enables researchers to isolate the impact of specific behavioral features—such as gaze direction, movement synchrony, or response delays—on group processes like leadership emergence, role differentiation, or collective decision-making. Unlike VR avatars, robots provide tangible, embodied presence, which can shape participants' psychological responses in unique ways, such as heightening perceptions of authority, trust, or even competition (Pan

& Steed, 2016). For example, in a tablet-based collaborative game with three participants, groups paired with a robot that made vulnerable statements engaged in substantially more conversation, distributed speaking turns more evenly, and evaluated their group more positively compared to groups with a robot that made only neutral or no statements at the end of each round (Traeger et al., 2020).

However, this approach is not without limitations. The artificial nature of the agent's behavior may limit external validity, especially if participants detect the manipulation. Thus, hybrid designs that combine real-time behavioral adaptation (e.g., reinforcement learning) with humanlike algorithms offer a promising middle ground.

Agent-Agent Interaction with Simulation

Group behavior evolves dynamically over time, and certain emergent properties—such as social conventions, cultural norms—often require large-scale temporal frameworks to be observed. Human-participant approaches are inherently limited in capturing such long-term dynamics due to practical constraints and ethical boundaries. At the far end of the experimental spectrum lies agent-agent interaction, typically implemented through computational simulations. In these models, autonomous agents are equipped with human-like attributes—such as cognitive biases, memory, and social preferences. Agent-based modeling (ABM) enables researchers to systematically manipulate agent-level rules to investigate how complex group phenomena emerge over extended time-scales, including scenarios that would be ethically impermissible with real participants (Goldstone & Janssen, 2005; Luo et al., 2008; Smith & Conrey, 2007). For instance, in a simulated fire evacuation task, each agent is programmed to escape during an emergency and select routes based on predefined parameters—such as humanlike knowledge of predictable spatial changes relevant to fire safety—allowing researchers to observe how conformity emerges and dynamically changes over time (Tan et al., 2015).

Since the introduction of segregation models, agent-based modeling (ABM) has enabled researchers to iteratively test hypotheses across diverse simulation parameters, revealing robust patterns and delineating boundary conditions for various group dynamics. Simulations also offer unparalleled scalability—thousands of agents can be run concurrently—providing a high-throughput platform for generating hypotheses and rigorously testing theories. ABM has been applied to investigate phenomena such as group formation, norm emergence, and crowd behavior. Gray et al. (2014) employed an ABM grounded in just two principles—reciprocity and transitivity—and demonstrated that agents, despite lacking any shared identity, nonetheless developed strong in-group cooperation and out-group defection. Similarly, Ye et al. (2021) incorporated inertia and trend-seeking mechanisms into their model to reproduce the macroscopic delay and explosive

adoption patterns commonly observed in real-world social diffusion processes.

Recent advances in large language models (LLMs) have substantially expanded the scope of agent-agent interaction studies by enabling agents with flexible, context-sensitive reasoning capacities. Unlike traditional rule-based or reinforcement learning agents that depend on fixed strategies, LLM-driven agents can dynamically interpret instructions, attend to contextual cues, and generate adaptive responses without relying on hard-coded behavioral scripts (Gao et al., 2024). This flexibility allows them to engage in complex social behaviors such as negotiation, role-taking, norm learning, and even cultural transmission, making their group-level dynamics more comparable to those observed in human collectives (Abdurahman et al., 2024). They can also produce language-based justifications, explanations, or persuasive arguments—introducing communicative mechanisms often absent from classical agent-based models (Gao et al., 2024). This opens avenues to study not only what group-level outcomes emerge (e.g., consensus, polarization, cooperation) but also how these outcomes are linguistically constructed and sustained. Moreover, platforms integrating multiple LLM agents—each with distinct roles, goals, or biases—have demonstrated spontaneous emergence of social phenomena such as group norms, hierarchies, and even proto-cultures (e.g., Acerbi & Stubbersfield, 2023; Ashery et al., 2025; Park et al., 2023). For example, Ashery et al. (2025) implemented an LLM-based naming game in which agents drew on accumulated memory of past choices to anticipate their partners' responses. This pairwise coordination process led to collective biases—such as stable naming conventions—that could not be inferred from isolated agent behavior. By systematically manipulating agent parameters (e.g., memory span, social preference, susceptibility to influence), researchers can now test theories of group psychology at scales and timescales unfeasible with human participants alone.

Ecological exploration of group behavior through agent-agent simulations depends heavily on the algorithms that govern each agent. While LLM-based agents offer a powerful means to simulate collective actions, they often lack the rich personal characteristics and lived experiences of real humans. To enhance realism and predictive validity, these simulations should be augmented with empirical human data—such as behavioral traces, cognitive profiles, and social network information—thereby grounding algorithmic agents in authentic human diversity and complexity.

Future Directions for Studying Group Behavior

The three approaches, each involving different levels of algorithmic agents, address the limitations of traditional experimental methods by offering more control while

preserving ecological validity. They provide a unified methodological framework for studying group behavior. However, there are several promising directions for future research.

These approaches should be integrated rather than treated as separate methods, as they complement each other. For example, when studying social conformity, human-human interactions with controlled agents can reveal the fundamental principles that govern conformity. To further examine how these principles operate, researchers could introduce algorithmic agents, either with or without knowledge of the principle, and observe the effects on conformity. Finally, to explore the role of these principles on a larger scale, ABM can be used by setting different parameters for the agents, simulating a broader range of scenarios.

Algorithmic agents should be designed with more humanlike parameters. The success of simulating human behavior depends significantly on how avatars are parameterized, which can be derived from observing group behavior. Importantly, human cognition develops gradually, and individuals at different developmental stages exhibit varying cognitive mechanisms. For instance, the ability to understand others' thoughts (theory of mind) typically emerges around the age of 4 (Wellman, 2014). While LLMs provide humanlike responses, they still face challenges, such as hallucinations. Furthermore, cognitive abilities vary among individuals, and this variation should be accounted for when designing agents.

Finally, these three experimental approaches should be combined with advanced data collection techniques. Recent advances in data collection, such as wearable sensors and online behavioral traces, enable the capture of fine-grained behavioral responses and high-dimensional, multi-modal data on group behavior (Hałgas et al., 2023). The diversity of data allows for multiple forms of evidence to examine how individual-level cognitive and motivational processes link with group-level emergent outcomes. Additionally, when combined with ABM, these data can be used to develop predictive models of group performance, cohesion, and breakdown.

Conclusion

Together, these three approaches—human-human interaction with controlled agents, human-agent interaction with algorithm-driven action, and agent-agent interaction through simulation—form a methodological continuum for studying group behavior. Each offers unique strengths: ecological validity, experimental control, and scalability. When combined, they provide a comprehensive toolkit for linking individual cognition to collective dynamics, enabling a deeper understanding of how groups form, function, and adapt in complex social environments.

Future research should focus on integrating these approaches, where humans and intelligent agents interact

within controlled yet realistic scenarios, designing algorithmic agents with more humanlike parameters, and combining them with advanced data collection techniques. Such interdisciplinary approaches will be essential for unraveling the link between micro-level individual cognition and macro-level collective behavior patterns, thereby contributing to a deeper understanding of complex group behaviors.

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Author Contributions

Jun Yin: Conceptualization, writing—original draft, writing—review and editing; **Hui Chen:** Writing—review and editing; **Junying Liang:** Conceptualization, writing—original draft, writing—review and editing.

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Artificial Intelligence

During the writing of this paper, we used ChatGPT 3.5 to enhance readability and improve the clarity of language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

This research did not generate data.

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