Tsinghua Science and Technology
Doi: 10.26599/TST.2026.9010040

Research Article

Experimental evidence on the emergent social network patterns of LLM-driven multi-agent system for edge service collaboration

Weiyue Chen, Guoshuai Zhang (✉), Jiaji Wu, and Gwanggil Jeon

Abstract As a common phenomenon that stable social structures emerge in real societies, an important question is whether similar non-random collaboration patterns can arise in large language model (LLM)-driven multi-agent system deployed in intelligent edge environments without explicit social rules. Therefore, we develop a round-based multi-agent simulation platform in which LLM-driven agents engage in long-term interactions. The interaction process produces an evolving directed social network for subsequent structural analysis. Specifically, we analyze the emergent structures based on over 200,000 simulation records. At the macro level, internal relationship strength decreases with increasing team size, indicating the emergence of a diseconomies-of-scale effect analogous to that observed in real organizations. From the micro perspective, agents are more likely to form new relationships when sharing common interaction partners, exhibiting a pronounced triadic closure effect relative to random baselines. Furthermore, robust reciprocal interaction patterns emerge with balanced dependence between agents promoting the formation of stable bidirectional relationships, consistent with power-dependence theory. Finally, these results demonstrate that even in the absence of predefined social mechanisms, LLM-driven multi-agent system operating in edge-inspired distributed settings can spontaneously generate meaningful network structures, supporting their use in the design of scalable and cooperative LLM agent society.

Keywords multi-agent system; large language model; social network patterns; emergent collaboration; edge computing

• Weiyue Chen, Guoshuai Zhang, and Jiaji Wu are with the School of Electronic Engineering, Xidian University, Xi'an, Shaanxi 710071, China. E-mail: 24021211472@stu.xidian.edu.cn; zhangguoshuai@xidian.edu.cn; wujj@mail.xidian.edu.cn.
• Gwanggil Jeon is with the School of Electronic Engineering, Xidian University, Xi'an, Shaanxi 710071, China and Department of Embedded Systems Engineering, Incheon National University, Incheon, 22012, Korea. E-mail:gjeon@inu.ac.kr.
* To whom correspondence should be addressed.
Manuscript received: 2025-12-30; revised: 2026-02-21; accepted: 2026-04-20

1 Introduction

In recent years, multi-agent system driven by large language models (LLMs) have been widely adopted to study complex decision-making, collaboration, and strategic interactions [1, 2, 37, 39]. By enabling multiple agents with natural language understanding and generation capabilities to engage in sustained interactions, such systems are increasingly regarded as a promising framework for modeling collective behaviors in real-world social systems [3]. In this context, understanding such multi-agent system's social pattern in repeated interactions is critical for revealing the internal mechanisms of group collaboration and for improving the overall efficiency and robustness. Analyzing the agent relationships not only facilitates the interpretation of emergent collective behaviors, but also provides structural insights for designing scalable and stable multi-agent systems. However, existing studies have primarily focused on task performance and strategic outcomes, while the social network patterns that emerge from long-term interactions among agents remain largely underexplored. As a result, a fundamental question remains unanswered: can LLM-driven multi-agent systems emerge meaningful sociology principles solely through local interactions in the absence of explicit rules, external incentives, and structural constraints.

In real social systems, group structures do not emerge randomly, but instead exhibit a set of stable and reproducible patterns. For instance, as group size increases, the average strength of internal relationships and overall structural cohesion tend to decline [4]; interpersonal ties are more likely to form between individuals who share common neighbors, a phenomenon known as triadic closure [5]; and interaction networks often display reciprocity and balanced dependence between actors [6]. These patterns have been widely recognized in social network studies as fundamental mechanisms. If multi-agent systems are to serve as effective tools for social science, it is therefore essential to examine whether such canonical structural patterns can naturally arise from multi-agent interactions.

Although prior studies has demonstrated the emergence of complex behaviors in multi-agent systems, quantitative analyses at the level of social network structure remain limited [7, 8]. On the one hand, many studies lack explicit network representations of agent relationships, making it difficult to conduct systematic comparisons across experiments. On the other hand, even when network analysis is employed, structural patterns are often not evaluated against appropriate random baselines, which obscures whether observed phenomena are driven by genuine interaction mechanisms or merely by heterogeneous activity levels. Consequently, it remains unclear whether the relationship patterns observed in multi-agent systems reflect endogenous social mechanisms or are artifacts of random processes.

To address these limitations, we develop a multi-agent simulation platform, in which agents driven by LLMs interact over multiple rounds and dynamically form and update social relationships. The resulting agent society is formalized as a directed weighted network, and social relationship is extracted before and after the simulation to enable systematic analysis of network evolution. Moreover, our comprehensive analysis framework integrates macro- and micro-level perspectives, combining graph metrics to examine the generative mechanisms and structural properties of multi-agent social networks. To summarize, the main contributions of this article are as follows.

1) We develop a multi-agent simulation platform driven by large language models, in which agents dynamically update social relationships during the interaction process, and generate a dataset of over 90,000 interaction records. The platform represents agents' relationships as a weighted social network. This enables quantitative analysis of network evolution and emergent social network patterns from multiple perspectives.
2) We propose a network-based analysis framework to assess and verify the relationships between team size and internal strength of agents from a macro perspective. The experimental results show that structural cohesion decreases as team size increases. This finding demonstrates that LLM-driven multi-agent system can reproduce macro-level diseconomies of scale effect observed in real organization.
3) We perform a comprehensive analysis of the triadic closure and reciprocity for social networks composed of agents at the micro level. The results show that multi-agent system exhibits a significant tendency toward triadic closure and stable reciprocal interactions beyond degree-preserving random baselines, which indicates that typical social mechanisms can emerge in multi-agent system through language-driven local interactions.

The rest of this article is organized as follows. Related works on multi-agent systems and social network analysis is reviewed in Section 2. Then, the multi-agent interaction platform and the methodology for modeling and analyzing agents' relationships are presented in Section 3. In Section 4, we present the experimental results and compare the observed structural patterns with appropriate baselines. Finally, Section 5 discusses social emergence in multi-agent systems and its implications for multi-agent system design.

2 Related Works

2.1 LLM-driven Multi-agent Systems and Simulation Frameworks

Large language model-driven multi-agent systems have recently been widely adopted to study complex collective behaviors and social interactions. Existing studies indicate that current multi-agent systems enable the simulation of collaborative behavioral processes with a certain degree of complexity [1, 2, 7, 9]. Compared with traditional multi-agent models based on hand-crafted rules or fixed strategies, LLM-based agents exhibit greater flexibility in contextual understanding and action generation, allowing them to display interaction patterns that more closely resemble those of humans in open environments [10, 11, 38, 40].

At the system level, a variety of LLM-based multi-agent simulation frameworks have been proposed to explore cooperation, strategic interaction, and social behavior. Generative agents have been used to model virtual individuals endowed with memory and planning abilities, enabling stable interaction patterns to emerge through continuous communication [12, 13]. In strategic game settings, the integration of language models with planning and reasoning mechanisms allows agents to construct alliances and coordinate actions via natural language, achieving performance comparable to that of human players [14, 15]. In addition, role-playing multi-agent frameworks have demonstrated the effectiveness of language-driven interaction in collaborative tasks [16]. Related studies further suggest that LLM agents can partially substitute for human participants in behavioral experiments, with collective decision outcomes showing a high degree of consistency with those observed in human studies [9, 17, 18]. To support such investigations, several platforms have been developed to facilitate long-term multi-agent interactions and to record group-level behaviors [19–22]. Overall, existing work has primarily evaluated system capabilities from the perspectives of behavioral plausibility or task performance.

Meanwhile, traditional multi-agent systems and agent-based modeling have long emphasized the role of social

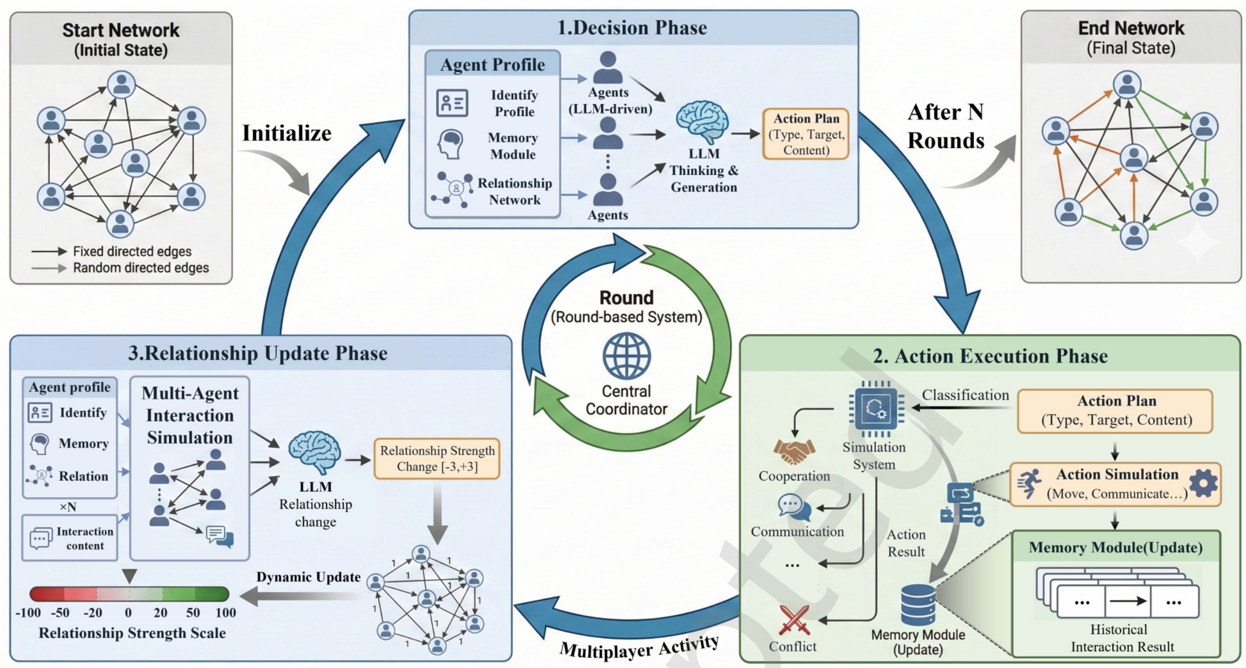

Fig. 1 Overview of the LLM-driven multi-agent interaction framework. The framework consists of a centrally coordinated, round-based multi-agent interaction process for social network generation. Agents are initialized with partially fixed and randomly generated directed relationships. In each round, agents sequentially perform decision-making, action execution, and relationship updating based on their profiles, memory, and existing relationships. Interaction outcomes are recorded and translated into updates of directed relationship weights, driving the evolution of the social network from the initial state to the final state over multiple rounds.

structure and relational networks in shaping collective behavior. However, these models typically rely on explicit rules, fixed strategies, or exogenous incentives, with social structure often treated as a prior assumption rather than an emergent outcome [13, 14]. In contrast, social network analysis and sociological research have consistently shown that real-world social networks exhibit stable non-random structural patterns, including triadic closure, homophily, reciprocity, and structural dilution associated with increasing group size [23–26]. These structural regularities are commonly regarded as key theoretical benchmarks for assessing whether a system possesses meaningful social modeling capacity.

2.2 Structural Perspectives in LLM-driven Agent Societies

In recent years, LLM-driven multi-agent systems have also been explored across diverse domains beyond structural analysis. For instance, agent societies have been investigated in structured gameplay environments to analyze collaboration and confrontation behaviors among language model agents [31]. Other studies have examined collaboration strategies and coordination mechanisms in multi-agent systems to improve collective task performance [32]. Domain-specific applications have further demonstrated the effectiveness of multi-agent collaboration in areas such as financial forecasting [33], industrial fault diagnosis [34], knowledge-enhanced biomedical modeling [35], and edge computing [36].

While these studies highlight the expanding application scope of LLM-based multi-agent systems, they primarily emphasize task-oriented optimization, performance enhancement, or domain-specific objectives. In contrast, this article focuses on the endogenous emergence of social relationship networks under long-term free interaction, aiming to examine structural evolution from a social network perspective.

A limited number of studies have begun to introduce a structural perspective into LLM-based multi-agent systems. Some work has examined the ability of language model agents to form social norms and shared conventions through interaction, while also highlighting the potential accumulation of biases [27, 28]. Other studies report that under free interaction conditions, agent networks may exhibit global or local structural features similar to those observed in real social networks, such as homophily and triadic closure [26, 29, 30]. However, these efforts remain fragmented, often lacking systematic modeling of long-term network evolution and rigorous comparisons against appropriate random baselines.

Overall, existing studies on large language model–driven multi-agent systems have primarily focused on task perfor-

Fig. 2 Multi-agent interaction simulation platform driven by large language models.

mance and behavioral plausibility. More recently, a small number of works have begun to note that agents engaged in sustained interactions may exhibit certain social phenomena, such as changes in interaction patterns or increasing consistency in group behavior. However, these analyses are often limited to local observations and lack systematic modeling of long-term relationship evolution as well as rigorous comparisons with random baselines. As a result, whether multi-agent systems can, in the absence of explicit social rules and external incentives, spontaneously form stable relationship network structures through long-term interaction remains an open empirical question. Motivated by this gap, this study investigates the evolution of relationship networks in large language model–driven multi-agent systems through controlled experiments.

3 Methodology

We develop a multi-agent interaction framework driven by LLMs for social network pattern analysis, in which agents operate within a centrally coordinated, round-based system. Moreover, agents iteratively complete three stages in each round, including decision-making, action execution, and relationship update. Through the joint effects of repeated interactions and the evolution of agent memory, the framework enables the dynamic formation and evolution of a global social network structure, as illustrated in Fig. 1.

In this section, we first introduce the construction of the multi-agent simulation platform. We then conduct quantitative analyses of the multi-agent social networks at different structural levels. Specifically, we analyze the relationship between team size and internal relationship strength to demonstrate the emergence for diseconomies of scale from macro level. At the micro level, we subsequently analyze triadic closure and reciprocity in multi-agent social networks.

3.1 Multi-Agent Simulation Platform

To examine sociological regularities emerging from group interactions, we construct a multi-agent interaction platform for generating dynamically evolving agent social networks, as shown in Fig. 2. The platform consists of a group of agents driven by large language models. Through sustained interactions during the simulation, agents form a social network that is continuously updated across successive rounds.

As illustrated in Fig. 1, the platform adopts a round-based scheduling mechanism. The system proceeds to the next round only after all agents complete the current round. Each agent is equipped with an independent profile containing attributes such as name, gender, role, personal description, and team affiliation. These attributes constitute the core contextual information used for subsequent action decision-making. For formal representation, the social network is modeled as a directed weighted graph, where relationships between agents are represented as directed edges with associated weights, as shown in Fig. 3.

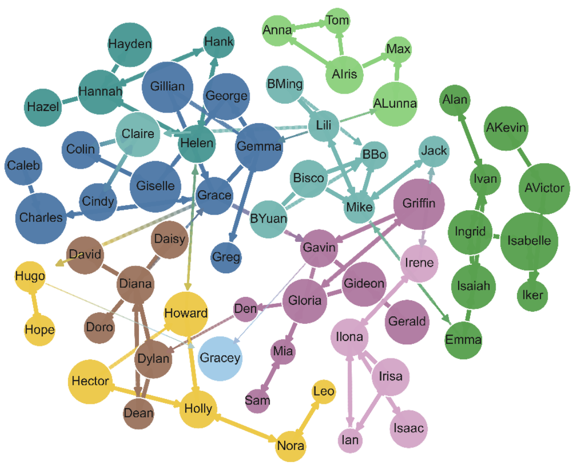

Fig. 3 Illustration of the directed weighted agent social network. Nodes represent individual agents, and directed edges represent interpersonal relationships between agents. Edge direction indicates the direction of interaction, while edge weight reflects the strength of the relationship.

Each simulation round consists of three consecutive stages: a decision phase, an action execution phase, and a relationship update phase. In the decision phase, each agent generates a planned action for the current round. The decision is based on the agent's profile, existing relationships, and historical interactions stored in the memory module, using a large language model. In the action execution phase, the system parses and executes the planned actions, extracts the action type and target agent, and records the outcomes in the memory module, allowing them to influence future agent decisions.

The relationship update phase translates interaction content into changes in the social network structure. When an agent's action involves other agents, the system triggers a multi-agent interaction inference based on the action content, existing relationships between the agents, and relevant memory information. The large language model determines whether relationship weights should be updated according to the semantic outcome of the interaction. The model outputs an integer value Δw_{uv} in the range $[-3, 3]$ as the change in relationship strength from agent u to agent v, indicating the relationship variation induced by the interaction. Let the directed relationship strength from agent u to agent v be denoted as w_{uv}, with its value constrained to the range $[-100, 100]$. The system then updates the weight of the corresponding directed edge as $w_{uv} = w_{uv} + \Delta w_{uv}$.Through this process, inter-agent relationships are continuously accumulated and adjusted during the simulation, gradually forming a social network structure suitable for quantitative analysis.

At the beginning of the simulation, the platform generates a set of partially fixed relationships and randomly initialized relationships for all agents, forming the initial relationship network (start). After the predefined number of rounds is completed, the system exports all relationship strengths to construct the final relationship network (end). The macro-level and micro-level structural analyses in this study are based on comparisons between the initial and final networks. These comparisons enable the investigation of network evolution and social relationship formation mechanisms.

3.2 Diseconomies of Scale

Diseconomies of scale constitute a core phenomenon in social network and organizational research. The concept refers to the tendency for average relationship strength and structural cohesion to decline as group size increases. In real-world organizations, large-scale groups often face reduced collaboration efficiency due to rising communication costs, increasing internal heterogeneity, and the increasing sparsity of interpersonal relationships. As a result, expansion in scale does not necessarily lead to higher organizational efficiency. Examining whether this regularity can emerge spontaneously in multi-agent systems is essential. This analysis helps assess whether agent collectives can reproduce organizational mechanisms observed in real societies. It also provides insights into the structural limits of collaboration in large-scale artificial intelligence systems.

At the macro level, we examine the systematic relationship between team size and internal relationship strength based on the final relationship network. Let s_i denotes team size, defined as the number of agents in team i. Let I_i denotes team cohesion, which is defined as the average strength of internal relationships within team i and is computed as follows,

$$I_i = \frac{1}{|E_i|} \sum_{(u,v)\in E_i} |w_{uv}| \tag{1}$$

where E_i represents the set of all directed edges within team i, and w_{uv} denotes the interaction strength from agent u to agent v.

To further investigate the micro-level mechanisms underlying the scale effect, we introduce an individual-level supplementary analysis within teams. The marginal contribution of agent u to team i is defined as

$$M_i^u = I_i - I_i^{(-u)} \tag{2}$$

where M_i^u denotes the marginal contribution of agent u to the cohesion of team i, I_i is the original average internal relationship strength of the team, and $I_i^{(-u)}$ is the average internal relationship strength after removing agent u and all its associated relationships from the team network. If $M_i^u > 0$, the presence of agent i increases team cohesion. Conversely, if $M_i^u < 0$, removing the individual leads to higher team cohesion, indicating that the individual exerts a negative contribution to the team's structural cohesion.

3.3 Triadic Closure

Triadic closure is a common mechanism of relationship formation in social networks, referring to the tendency for two individuals who share common neighbors to form a new connection through subsequent interactions. This mechanism is widely observed in real-world social systems and is closely associated with trust accumulation, information diffusion, and the establishment of cooperative relationships. Examining whether triadic closure can emerge naturally in multi-agent systems helps assess whether the patterns of relationship evolution among agents resemble the micro-level structural characteristics observed in real social networks.

We quantify the probability of triadic closure by analyzing changes in interpersonal relationships between the initial relationship network and the final relationship network. The closure probability is defined as

$$P_{\text{close}}(k) = \frac{C_k}{N_k} \tag{3}$$

where N_k denotes the number of agent pairs that are not connected in the initial network but share k common neighbors, and C_k denotes the number of newly formed edges between such agent pairs in the final network. Accordingly, $P_{\text{close}}(k)$ represents the probability that two individuals with k common neighbors eventually establish a new connection.

To further examine whether identity homophily influences the probability of triadic closure, we partition agents into communities based on their initial profiles. For each potential agent pair (u, v), we define

$$\text{same}(u, v) = \begin{cases} 1, & \text{if} c_u = c_v, \\ 0, & \text{if} c_u \neq c_v. \end{cases} \tag{4}$$

where c_u and c_v denote the communities to which agents u and v belong, respectively. When $\text{same}(u, v) = 1$, the two agents are regarded as belonging to the same community. For each value of the number of common neighbors k, we compute closure probabilities separately for same-community and cross-community agent pairs. This comparison allows us to assess the effect of identity homophily on triadic closure.

The corresponding closure probabilities are computed as

$$P_{\text{close}}^{\text{same}}(k), \quad P_{\text{close}}^{\text{diff}}(k) \tag{5}$$

To determine whether the observed triadic closure effect exceeds what can be expected from the degree distribution alone, we adopt a degree-preserving null model as the baseline. In this model, the in-degree and out-degree of each node are preserved, while edges are randomly rewired between nodes to generate a set of reference networks. The closure probabilities obtained from these null networks are used as baseline values to evaluate whether triadic closure in the observed network is significantly higher than random expectations, thereby verifying that the effect arises from the interaction process among agents rather than being solely driven by node activity levels.

3.4 Reciprocity

At the micro level, we focus on reciprocity in multi-agent relationship networks. Reciprocity refers to the tendency of two individuals to respond to each other in interactions, such that when one individual invests in another, the latter is more likely to provide a corresponding return. In real social systems, reciprocity serves as an important norm for maintaining trust, stabilizing cooperation, and sustaining long-term relationships. If stable reciprocal structures can emerge spontaneously in multi-agent systems without explicit external constraints, this would indicate that large language model-driven agents are able to reproduce micro-level interaction mechanisms observed in real societies. Conversely, if reciprocity is largely absent, it would suggest clear limitations in the current system's ability to model social behavior.

For quantitative analysis, we first define the reciprocity rate based on the final relationship network. The reciprocity rate is defined as

$$R_{count} = \frac{F}{E} \tag{6}$$

where E denotes the total number of directed edges in the final relationship network, and F denotes the number of directed edges that have a corresponding reverse edge. This metric measures the proportion of bidirectional relationships among all relationships in the network.

To characterize reciprocity at the level of interaction strength, we further define the individual weighted reciprocity rate. The individual weighted reciprocity rate is defined as

$$R_u = \frac{\sum_{v \neq u} \min(|w_{uv}|, |w_{vu}|)}{\sum_{v \neq u} |w_{uv}|} \in [0, 1] \tag{7}$$

where w_{uv} denotes the interaction strength from individual u to individual v. The numerator takes the smaller value of each pair of bidirectional interactions, representing the mutually invested portion shared by both individuals, while the denominator corresponds to the total outgoing interaction strength of individual u toward all other agents. Accordingly, values of R_u closer to 1 indicate that most of an agent u's investments are reciprocated, whereas values closer to 0 indicate predominantly unilateral output.

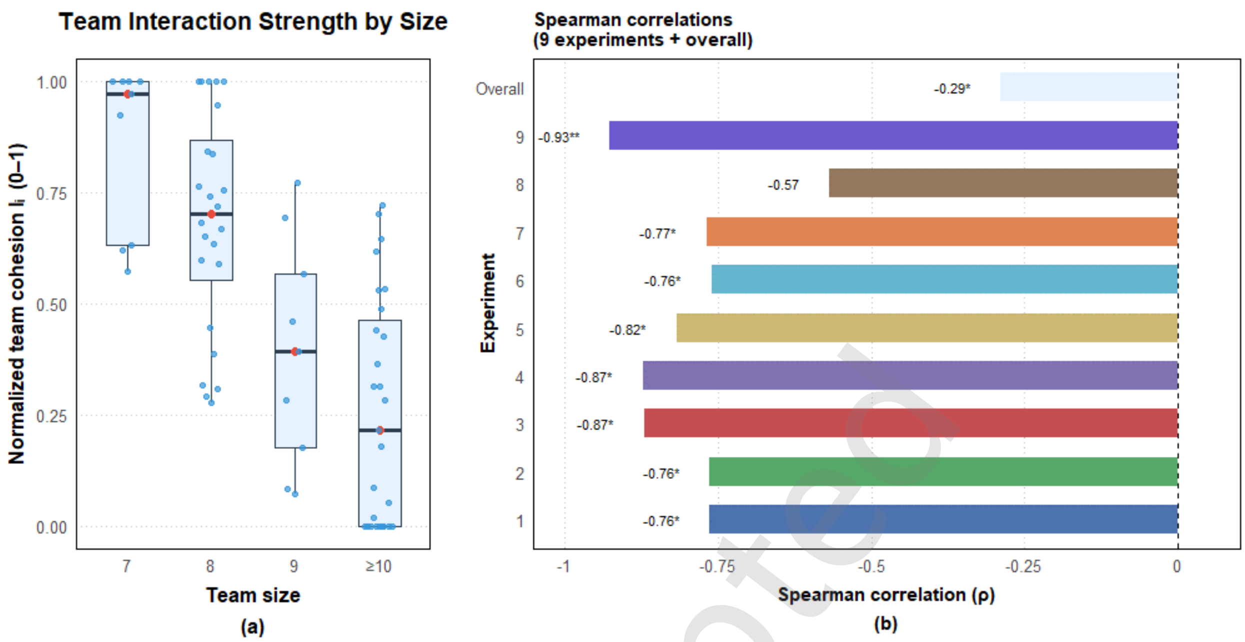

Fig. 4 Relationship between team size and internal team cohesion. The left panel (a) shows the distribution of normalized team cohesion for teams of different sizes aggregated across nine experiments, while the right panel (b) reports Spearman correlation coefficients for each experiment and for the overall dataset.

At the global level, we define the global weighted reciprocity rate as

$$R_{weight} = \frac{2 \sum_{(u,v)} \min(|w_{uv}|, |w_{vu}|)}{\sum_{(u,v)\in E} |w_{uv}|} \in [0,1] \tag{8}$$

The numerator is computed as the reciprocal strength of each bidirectional interaction, defined as the minimum of the two corresponding edge weights, while the denominator is the total interaction strength in the final relationship network.

To assess whether the observed reciprocity effect exceeds what can be expected from the degree distribution alone, we adopt a degree-preserving null model as the structural baseline. In this model, the in-degree and out-degree of each node are kept fixed, while edges are randomly rewired between nodes to generate a set of reference networks. We compute the corresponding R_{count} and R_{weight} on these null networks and compare them with the observed values in the real network to determine whether the level of reciprocity is significantly higher than random expectations under fixed node activity.

To further investigate the internal mechanisms underlying the formation of reciprocity, we introduce Emerson's power-dependence theory. This theory posits that the more symmetric the mutual dependence between two actors, the more balanced their power relationship, and the more likely it is for reciprocal relationships to form and persist. When dependence is highly asymmetric, power becomes concentrated on one side, and relationships are more likely to evolve into unilateral investments rather than stable reciprocity.

In the final relationship network, we characterize dependence structures using the following measures. Total outgoing strength represents the total investment strength of agent toward all other agents and is defined as

$$S_{\text{out}}(u) = \sum_{x} w_{ux} \tag{9}$$

Dependence share is defined as

$$D_{u\to v} = \frac{w_{uv}}{S_{\text{out}}(u)} \in [0,1] \tag{10}$$

which represents the proportion of agent u's total investment that is directed toward agent v. A larger value indicates that agent v occupies a more important position in u's external interactions. when v is removed, u exhibits almost no interaction with others.

Dependence asymmetry is defined as

$$D_{abs} = |D_{u\to v} - D_{v\to u}| \tag{11}$$

which quantifies the degree of imbalance in mutual dependence between a pair of agents. Values closer to 0 indicate more symmetric dependence, whereas values closer to 1 indicate highly unilateral dependence. By using dependence asymmetry to predict whether a relationship forms reciprocity, we can test the applicability of power-dependence theory in multi-agent relationship networks and evaluate the role of dependence structure in the generation of reciprocal ties.

4 Experimental Results and Analysis

4.1 Dataset

Based on the self-developed multi-agent simulation platform, this study conducts a total of nine independent experiments. In each experiment, 64 agents are deployed and the system is executed for 150 rounds. In every round, all agents perform decision-making and action execution, resulting in structured behavioral logs. Across the nine experiments, more than 90,000 raw behavioral records are generated. As many actions involve interactions among multiple agents, expanding these records into relationship-level changes yields over 200,000 instances of relationship updates.

Each record contains fields including the acting agent, the target agent, the action category, and the interaction content, enabling a complete representation of agents' decision behaviors and interaction outcomes within the social environment. Overall, this study constructs a multi-agent social interaction dataset at the scale of hundreds of thousands of records, providing sufficient support for macro- and micro-level network structure analyses. All experiments are driven by the DeepSeek-R1 model.

4.2 Diseconomies of Scale in LLM-driven Multi-agent Social Network

To examine whether team size affects internal structural characteristics, we compute team cohesion I_i based on the dataset described in Section 4.1 and analyze the relationship between team size and team cohesion. The results are shown in Fig. 4. The left panel of Fig. 4 presents the distribution of team cohesion I_i for teams of different sizes, aggregated across the nine experiments. Overall, smaller teams exhibit higher levels of team cohesion I_i, whereas cohesion decreases markedly as team size increases, accompanied by substantially greater variability.

The Spearman correlation results shown in the right panel further indicate that the correlation coefficients are significantly negative in most experiments, ranging approximately from -0.70 to -0.90. The aggregated statistics across all nine experiments similarly yield a negative correlation. These results indicate that larger teams tend to exhibit weaker internal interactions, with structural cohesion systematically declining as team size increases, consistent with a typical diseconomies-of-scale effect.

To further explain the micro-level mechanisms underlying this scale effect, we examine whether individual-level structural characteristics can predict an individual's marginal

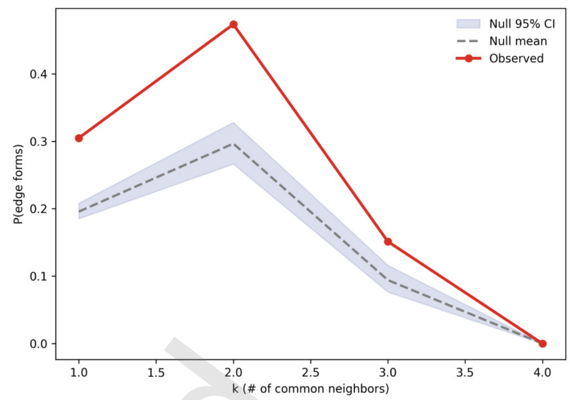

Fig. 5 Triadic closure probability as a function of the number of common neighbors, with comparison to the null model. The solid line shows the observed closure probability, while the dashed line and shaded area indicate the mean and 95% confidence interval of the degree-preserving null model, respectively.

contribution M_i^j to team cohesion. Specifically, we test the correlations between an individual's number of external connections, the strength of external connections, and M_i^j.

In the pooled sample across experiments, the number of external connections is significantly positively correlated with marginal contribution ($\rho = 0.164, p < 0.01$), indicating that individuals with more external connections tend to play more important bridging roles in the network, and their presence is more critical to internal team cohesion. In contrast, the correlation between external connection strength and marginal contribution is not statistically significant ($\rho = 0.053, p = 0.300$), suggesting that the intensity of external ties alone is not a decisive factor.

Taken together, these results indicate that the primary factor influencing marginal contribution is the number of connections rather than the strength of external connections. Individuals with more cross-team links are more likely to serve as structural bridges, thereby making greater contributions to team cohesion.

4.3 Triadic Closure in LLM-driven Multi-agent Social Network

We first examine whether the multi-agent relationship network exhibits an increasing probability of triadic closure as the number of common neighbors k increases. Fig. 5 presents the probability of new edge formation under different numbers of common neighbors and compares the results with those obtained from a degree-preserving null model.

As shown in Fig. 5, the closure probability in the observed network increases markedly within the range of $k = 1$ to $k = 2$, indicating that agent pairs with more common neighbors are more likely to establish direct connections in the final

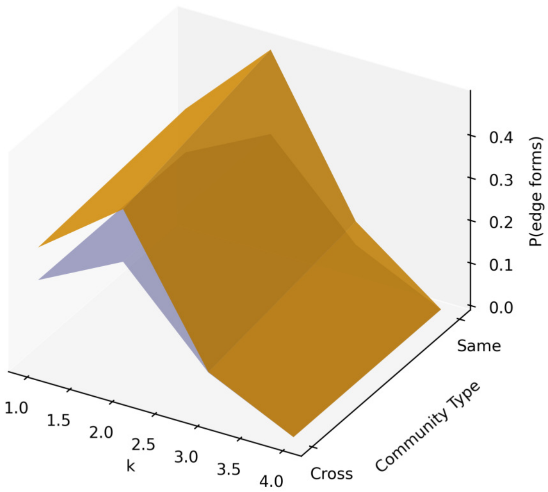

Fig. 6 Closure probability for same- and cross-community node pairs under different numbers of common neighbors.

network. In contrast, the closure probability in the null model varies only slightly with k and remains substantially lower than the observed values. The shaded area represents the 95% confidence interval generated by the null model, and the observed closure probabilities exceed this interval for all observable values of k, indicating that the triadic closure effect is robust across simulations.

At larger values of $k (k = 4)$, the observed decline in closure probability is mainly attributable to the small sample size, which leads to unstable estimation, and does not affect the overall trend. Aside from this boundary case, the observed network consistently exhibits a substantially stronger closure tendency than the random baseline, suggesting that typical local triangular structures in social networks can emerge spontaneously through multi-agent interactions.

After examining the structural effect of the number of common neighbors k on closure probability, we further investigate whether community homophily alters the tendency of triadic closure formation. Based on identity-based community assignments in the initial network, we classify all potential triadic node pairs into same-community and cross-community pairs, and compute their probabilities of forming new edges under different values of k. Fig. 6 illustrates the joint variation of closure probability with respect to k and community type.

As shown in Fig. 6, across all observable values of k, same-community node pairs consistently exhibit higher closure probabilities than cross-community pairs, with the most pronounced differences observed at $k = 1$ and $k = 2$. This indicates that homophily provides an additional reinforcing effect in the formation of triadic structures, making agents belonging to the same community more likely to establish direct connections given shared neighbors. In contrast, cross-

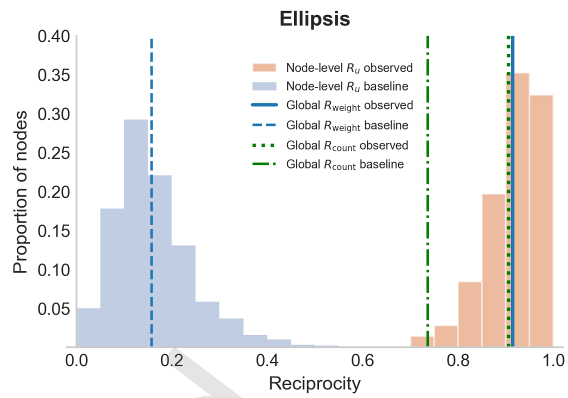

Fig. 7 Distributions of node-level and global reciprocity and comparison with the random baseline. Histograms show the distribution of node-level reciprocity, while vertical lines indicate observed and baseline values of global reciprocity measures.

community node pairs show lower closure probabilities for the same value of k, suggesting that community boundaries continue to impose structural constraints during evolution.

Qualitatively, we observe that small clusters gradually form during repeated interactions. Agents who share common collaborators tend to connect directly in later rounds, which creates more triangles. These triangles accumulate and lead to tightly connected subgroups in the evolving network.

Taken together, these results indicate that triadic closure formation is influenced not only by structural opportunities, as captured by the number of common neighbors k, but also by community structure. Under identical structural conditions, same-community node pairs are more likely to achieve closure, suggesting that agents spontaneously develop homophily preferences similar to those observed in real social networks. This preference strengthens the formation of triangular structures within communities while inhibiting closure across community boundaries, leading to pronounced group differentiation during network evolution.

4.4 Reciprocity in LLM-driven Multi-agent Social Network

Reciprocity is a fundamental basis for the stability of social relationships, reflecting whether individuals tend to respond to others' investments during interactions. To examine whether reciprocity mechanisms can emerge spontaneously in multi-agent systems under free interaction, we analyze reciprocity from both the distributional and structural perspectives.

We first examine node-level reciprocity R_u as well as global reciprocity R_{count} and R_{weight}, and compare their values with a degree-preserving random baseline. Fig. 7 presents the overall distributions of reciprocity. As shown in the figure, node-level reciprocity exhibits a pronounced

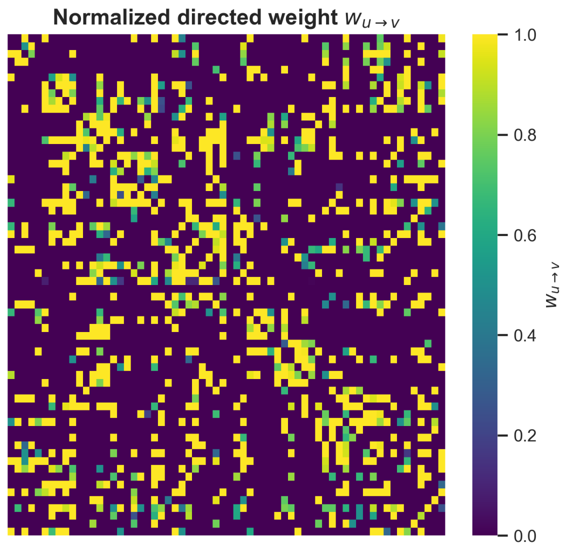

Fig. 8 Reciprocity matrix heatmap of directed interaction weights between agent pairs.

right-skewed distribution across all experiments, indicating that most agents receive corresponding responses to their investments in others. At the global level, the observed values of R_{count} and R_{weight} are both substantially higher than those of the random baseline, suggesting that the system exhibits a stable tendency toward bidirectional interactions. These results indicate that even in the absence of explicit rule constraints, agents spontaneously form reciprocity structures that exceed random expectations.

To further analyze the directional distribution of reciprocity between individual agent pairs, we construct a reciprocity matrix, as shown in Fig. 8. The heatmap reveals highly symmetric block-like patterns in regions with high values, indicating that when agent u exhibits a high level of investment toward agent v, the latter is likely to provide a corresponding response. This pairwise symmetry suggests that reciprocity does not arise uniformly or by chance, but instead concentrates in a set of stable reciprocal structures, reflecting the gradual emergence of balanced and norm-like interaction patterns during social interactions.

Taken together, both figures indicate that multi-agent systems can spontaneously evolve strong reciprocity mechanisms through sustained interactions, not only exhibiting levels significantly higher than those observed in random networks, but also displaying stable reciprocal patterns at the structural level. From a qualitative perspective, the reciprocity matrix further illustrates how reciprocal ties tend to cluster among subsets of agents with comparable interaction intensities. Over successive interaction rounds, these balanced exchanges gradually reinforce each other, forming stable bidirectional connections rather than transient or isolated reciprocal events.

This descriptive pattern complements the statistical findings by visually demonstrating the emergence of sustained reciprocal structures.

Building on the directional investment model introduced in Section 3.4, we further examine whether dependence structure influences the formation of reciprocal relationships. According to the power–dependence framework defined in Section 3.4, edge-level dependence asymmetry captures the relative balance of investments between two agents. Using the merged final relationship network, we conduct a logit regression analysis on a total of 2,726 edges, with reciprocity formation as the dependent variable, dependence asymmetry as the key independent variable, and other structural variables included as controls.

The regression results show that the mean coefficient of dependence asymmetry is -32.9 ($p < 0.01$), indicating a strong and significant effect. This result suggests that as dependence becomes more imbalanced and approaches unilateral investment, the probability of reciprocity formation in the final network decreases substantially. In other words, reciprocity is more likely to emerge in relationships where investments are relatively balanced and dependence is more symmetric, whereas large disparit1es in investment make reciprocal ties difficult to sustain or establish.

This pattern is highly consistent with Emerson's power–dependence theory, which posits that relationships with more symmetric mutual dependence are more conducive to stable bidirectional interactions, whereas highly asymmetric dependence tends to sustain unilateral relationships rather than evolving into reciprocity. Our results indicate that even under fully autonomous interaction conditions, multi-agent systems can spontaneously exhibit dependence–power dynamics similar to those observed in real social organizations, and that reciprocity mechanisms are not random outcomes but are systematically constrained by dependence balance within relationship structures.

5 Discussion

The experimental results of this study show that multi-agent systems, even in the complete absence of explicit social rules, are able to spontaneously evolve multi-level social structures through language-driven local interactions alone. These structures span macro-level organizational patterns, local mechanisms of relationship formation, and micro-level dynamics of reciprocity and dependence. The observed structural characteristics closely resemble those commonly found in real-world social networks, indicating that agents driven by LLMs possess an inherent capacity to form stable social relationships and complex interaction structures, rather than merely reproducing static patterns from training data.

More importantly, the emergence of these structures provides a new theoretical perspective for understanding the behavioral logic of agent collectives and offers important insights for the future design of scalable and cooperative large-scale multi-agent systems. In the following subsections, we discuss the deeper implications of the experimental results from three perspectives: macro-level organizational structure, micro-level relationship formation mechanisms, and reciprocity dynamics.

5.1 Evolution of Macro-level Structure: Emergence of Diseconomies of Scale

The experimental results show that larger teams exhibit weaker internal relationship strength, demonstrating a clear pattern of diseconomies of scale. This regularity is not imposed by any explicit mechanism in the platform design, yet it consistently emerges across multiple simulation runs, indicating that scale constraints arise as a macro-level property of agent relationship networks through autonomous interactions.

This finding directly supports the central premise of this study: multi-agent systems can spontaneously evolve structural regularities highly consistent with those observed in real organizations, relying solely on language-driven local interactions in the absence of external social rules. Although agents do not face explicit communication costs or coordination burdens by design, increasing group size nonetheless leads to difficulties in maintaining dense relationship structures. This suggests that "scale pressure" in organizational structures can emerge as a cumulative result of micro-level interactions, rather than requiring explicit institutional constraints.

At the same time, this pattern reveals inherent limitations faced by agent collectives as their scale expands. As the number of agents increases, attention and interaction opportunities become increasingly dispersed, making stable relationships harder to sustain and leading to a decline in overall group cohesion. This dynamic closely mirrors the increased complexity and reduced cooperation efficiency commonly observed in expanding human organizations. The results therefore suggest that the design of large-scale cooperative multi-agent systems should account for such endogenous cohesion loss, for example through role differentiation, information aggregation, or structural guidance mechanisms to maintain group stability.

In summary, the emergence of diseconomies of scale not only illustrates the macro-level dynamics of agent social structures, but also demonstrates that multi-agent systems are capable of generating empirically meaningful social phenomena. More importantly, it provides key implications for the scalability of future cooperative agent systems: organizational efficiency in large agent collectives is likewise constrained by structural factors, and system design must incorporate an understanding of group dynamics. In other words, the task allocation may benefit from organizing agents into moderately sized sub-teams rather than excessively large collectives.

5.2 Emergence of Relationship Formation Mechanisms (Triadic Closure and Homophily)

The experimental results show that multi-agent systems spontaneously exhibit a pronounced triadic closure effect during interactions, along with a stable tendency toward community homophily, whereby node pairs with common neighbors or shared community membership are more likely to form new relationships.

This finding further supports the core premise of this study: even in the absence of any explicit social rules or constraints, agent collectives can develop relationship formation mechanisms that closely resemble those observed in real social networks through language-driven local interactions alone. Triadic closure is commonly regarded as a natural outcome of trust accumulation, information transmission, and structural balance in human societies. In the present system, however, agents are not provided with any explicit modeling of closure structures, yet the same pattern emerges spontaneously. This indicates that triadic closure can arise naturally from localized contextual reasoning and accumulated interactions.

The emergence of community homophily further reflects agents' sensitivity to identity information and the amplification of structural effects over time. Although initial community labels are provided only as background attributes, agents consistently exhibit a preference for forming connections with members of the same community during interactions, leading to the gradual consolidation of community boundaries. This similarity-based attachment closely mirrors group differentiation mechanisms in real societies and provides a micro-level foundation for the formation of clustered network structures.

Taken together, the coexistence of triadic closure and homophily indicates that relationship formation in multi-agent systems is not random, but instead results from structured processes driven by logical reasoning, identity perception, and contextual interpretation. These micro-level mechanisms not only shape local network structures, but also lay the groundwork for macro-level patterns of organizational differentiation and cohesion change, further demonstrating the capacity of agent collectives to autonomously evolve complex network structures governed by social regularities.

5.3 Emergence of Reciprocity and Power-dependence Mechanisms

The experimental results show that reciprocity in multi-agent relationship networks is significantly higher than the random baseline, that reciprocal structures exhibit a high degree of symmetry, and that dependence asymmetry effectively predicts whether reciprocity emerges, with more balanced dependence increasing the likelihood of reciprocal ties.

This finding further reinforces the central premise of this study: even in the absence of any externally imposed cooperation norms, return rules, or power structures, agents are still able to spontaneously form stable reciprocal patterns through sustained language-based interactions. Reciprocity is widely regarded as one of the most fundamental micro-level mechanisms in social interaction, underpinning relationship maintenance, trust formation, and long-term cooperation. In the present system, agents are not endowed with any explicit principle requiring them to reciprocate. Nevertheless, both node-level and global reciprocity measures are significantly higher than those observed in the null model, indicating that reciprocal behavior emerges naturally from interaction context and accumulated relationships rather than from external incentives or institutional constraints.

The emergence of power–dependence structures provides a further mechanistic explanation for reciprocity formation. The logit regression results show that reciprocal ties are more likely to form when dependence between two agents is relatively symmetric, whereas dependence imbalance significantly reduces the probability of reciprocity. This pattern closely aligns with classical power–dependence theory in sociology, which posits that smaller power differentials facilitate the stability of cooperative relationships. In the multi-agent system, this suggests that agents implicitly evaluate relative dependence within relationships and adjust their responses in a manner consistent with balance-oriented reciprocity.

Taken together, the joint emergence of reciprocity and dependence structure reveals a micro-level mechanism underlying social behavior in agent collectives. Reciprocity enhances the stability of relationship networks, while dependence balance provides a structural regulatory principle. Their interaction supports the formation of more cohesive and sustainable bidirectional relationships. This mechanism not only closely parallels interaction patterns observed in real human societies, but also offers important implications for the design of future multi-agent systems: effective and stable cooperation at larger scales and higher task complexity requires the capacity to manage dependence relations and reciprocal behavior. In addition, the ability of LLM-driven agents to reproduce canonical social network mechanisms suggests that such systems can serve as experimental platforms for digital society simulation, enabling researchers to explore how group size or interaction settings influence network evolution under controlled settings.

6 Conclusion

In this article, we investigate the emergence of social network patterns in large language model-driven multi-agent system through long-term interactions. Specifically, we develop a multi-agent simulation platform driven by large language models, in which agents interact over multiple rounds and dynamically update directed and weighted social relationships. The interaction process generates a large-scale dataset with over 200,000 relationship update records, providing empirical support for analyzing the evolution of agent social networks without explicit social rules or external incentives. Furthermore, we propose a network-based analysis framework to examine the relationship between team size and internal relationship strength from a macro perspective. Experimental results consistently demonstrate that internal structural cohesion decreases as team size increases, revealing a clear diseconomies-of-scale effect and illustrating how group expansion influences collective interaction patterns. Finally, we perform a comprehensive micro-level analysis of triadic closure and reciprocity in agent social networks. The results show that agents exhibit a significant tendency toward triadic closure beyond degree-preserving random baselines, and that stable reciprocal relationships emerge under balanced dependence structures, which is consistent with classical social theories. These findings indicate that typical stable structures observed in real social systems can spontaneously emerge in multi-agent systems through language-driven local interactions alone.

Despite these findings, several limitations should be further explored. First, the experiments are conducted under a fixed interaction setting and a single model configuration (DeepSeek-R1), which may constrain the generalizability of the observed structural patterns. Moreover, the task environment and interaction framework are intentionally simplified to ensure experimental control. Future work will extend the current framework to multiple different LLMs, agents with varying capabilities, and more diverse task environments to systematically examine the robustness and boundary conditions of the emergent social network mechanisms.

Acknowledgment

This work was supported in part by China Postdoctoral Science Foundation under Grant 2024M752529, in part by the Postdoctoral Fellowship Program of CPSF under Grant GZC20232057, and in part by the National Natural Science Foundation of China under Grant 62271381.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

[1] X. Li, S. Wang, S. Zeng, Y. Wu, and Y. Yang, "A survey on llm-based multi-agent systems: workflow, infrastructure, and challenges," *Vicinagearth*, vol. 1, no. 1, p. 9, 2024.

[2] L. Wang, C. Ma, X. Feng, Z. Zhang, H. Yang, J. Zhang, Z. Chen, J. Tang, X. Chen, Y. Lin *et al.*, "A survey on large language model based autonomous agents," *Frontiers of Computer Science*, vol. 18, no. 6, p. 186345, 2024.

[3] J. De Curtò and I. De Zarzà, "Llm-driven social influence for cooperative behavior in multi-agent systems," *IEEE Access*, 2025.

[4] A. V. Carron and K. S. Spink, "The group size-cohesion relationship in minimal groups," *Small Group Research*, vol. 26, no. 1, pp. 86–105, 1995.

[5] J. S. Coleman, "Foundations of social theory," *Harvard Universit*, 1990.

[6] S. Wasserman, "Social network analysis: Methods and applications," 1994.

[7] C. Gao, X. Lan, N. Li, Y. Yuan, J. Ding, Z. Zhou, F. Xu, and Y. Li, "Large language models empowered agent-based modeling and simulation: A survey and perspectives," *Humanities and Social Sciences Communications*, vol. 11, no. 1, pp. 1–24, 2024.

[8] R. M. Emerson, "Power-dependence relations," in *Power in modern societies*. Routledge, 2019, pp. 48–58.

[9] G. V. Aher, R. I. Arriaga, and A. T. Kalai, "Using large language models to simulate multiple humans and replicate human subject studies," in *International Conference on Machine Learning*. PMLR, 2023, pp. 337–371.

[10] Q. Wu, G. Bansal, J. Zhang, Y. Wu, B. Li, E. Zhu, L. Jiang, X. Zhang, S. Zhang, J. Liu *et al.*, "Autogen: Enabling next-gen llm applications via multi-agent conversations," in *First Conference on Language Modeling*, 2024.

[11] S. Yao, J. Zhao, D. Yu, N. Du, I. Shafran, K. R. Narasimhan, and Y. Cao, "React: Synergizing reasoning and acting in language models," in *The Eleventh International Conference on Learning Representations*, 2022.

[12] J. S. Park, J. O'Brien, C. J. Cai, M. R. Morris, P. Liang, and M. S. Bernstein, "Generative agents: Interactive simulacra of human behavior," in *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*, 2023, pp. 1–22.

[13] J. S. Park, C. Q. Zou, A. Shaw, B. M. Hill, C. Cai, M. R. Morris, R. Willer, P. Liang, and M. S. Bernstein, "Generative agent simulations of 1,000 people," *arXiv preprint arXiv:2411.10109*, 2024.

[14] M. F. A. R. D. T. (FAIR)?, A. Bakhtin, N. Brown, E. Dinan, G. Farina, C. Flaherty, D. Fried, A. Goff, J. Gray, H. Hu *et al.*, "Human-level play in the game of diplomacy by combining language models with strategic reasoning," *Science*, vol. 378, no. 6624, pp. 1067–1074, 2022.

[15] G. Mukobi, H. Erlebach, N. Lauffer, L. Hammond, A. Chan, and J. Clifton, "Welfare diplomacy: Benchmarking language model cooperation," *arXiv preprint arXiv:2310.08901*, 2023.

[16] G. Li, H. Hammoud, H. Itani, D. Khizbullin, and B. Ghanem, "Camel: Communicative agents for" mind" exploration of large language model society," *Advances in Neural Information Processing Systems*, vol. 36, pp. 51 991–52 008, 2023.

[17] J. R. Anthis, R. Liu, S. M. Richardson, A. C. Kozlowski, B. Koch, E. Brynjolfsson, J. Evans, and M. S. Bernstein, "Position: Llm social simulations are a promising research method," in *Forty-second International Conference on Machine Learning Position Paper Track*.

[18] A. Filippas, J. J. Horton, and B. S. Manning, "Large language models as simulated economic agents: What can we learn from homo silicus?" in *Proceedings of the 25th ACM Conference on Economics and Computation*, 2024, pp. 614–615.

[19] G. Rossetti, M. Stella, R. Cazabet, K. Abramski, E. Cau, S. Citraro, A. Failla, R. Improta, V. Morini, and V. Pansanella, "Y social: an llm-powered social media digital twin," *arXiv preprint arXiv:2408.00818*, 2024.

[20] C. Gao, X. Lan, Z. Lu, J. Mao, J. Piao, H. Wang, D. Jin, and Y. Li, "S3: Social-network simulation system with large language model-empowered agents," *arXiv preprint arXiv:2307.14984*, 2023.

[21] A. Ferraro, A. Galli, V. La Gatta, M. Postiglione, G. M. Orlando, D. Russo, G. Riccio, A. Romano, and V. Moscato, "Agent-based modelling meets generative ai in social network simulations," in *International Conference on Advances in Social Networks Analysis and Mining*. Springer, 2024, pp. 155–170.

[22] G. M. Orlando, V. La Gatta, D. Russo, and V. Moscato, "Can generative agent-based modeling replicate the friendship paradox in social media simulations?" in *Proceedings of the 17th ACM Web Science Conference 2025*, 2025, pp. 510–515.

[23] M. Mosleh, D. Eckles, and D. G. Rand, "Tendencies toward triadic closure: Field experimental evidence," *Proceedings of the National Academy of Sciences*, vol. 122, no. 27, p. e2404590122, 2025.

[24] A. Z. Jacobs and D. J. Watts, "A large-scale comparative study of informal social networks in firms," *Management Science*, vol. 67, no. 9, pp. 5489–5509, 2021.

[25] E. Jahani, S. P. Fraiberger, M. Bailey, and D. Eckles, “Long ties, disruptive life events, and economic prosperity,” *Proceedings of the National Academy of Sciences*, vol. 120, no. 28, p. e2211062120, 2023.

[26] J. W. Burton, E. Lopez-Lopez, S. Hechtlinger, Z. Rahwan, S. Aeschbach, M. A. Bakker, J. A. Becker, A. Berditchevskaia, J. Berger, L. Brinkmann *et al.*, “How large language models can reshape collective intelligence,” *Nature Human Behaviour*, vol. 8, no. 9, pp. 1643–1655, 2024.

[27] A. F. Ashery, L. M. Aiello, and A. Baronchelli, “Emergent social conventions and collective bias in llm populations,” *Science Advances*, vol. 11, no. 20, p. eadu9368, 2025.

[28] A. Borah and R. Mihalcea, “Towards implicit bias detection and mitigation in multi-agent llm interactions,” *arXiv preprint arXiv:2410.02584*, 2024.

[29] M. Papachristou and Y. Yuan, “Network formation and dynamics among multi-llms,” *PNAS Nexus*, vol. 4, no. 12, p. pgaf317, 2025.

[30] G. De Marzo, L. Pietronero, and D. Garcia, “Emergence of scale-free networks in social interactions among large language models,” *arXiv preprint arXiv:2312.06619*, 2023.

[31] Y. Lan, Z. Hu, L. Wang, Y. Wang, D. Ye, P. Zhao, E.-P. Lim, H. Xiong, and H. Wang, “Llm-based agent society investigation: Collaboration and confrontation in avalon gameplay,” in *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, 2024, pp. 128–145.

[32] H. Wang, S. Zhao, J. Wang, Z. Qiang, B. Qin, and T. Liu, “Beyond frameworks: Unpacking collaboration strategies in multi-agent systems,” in *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics*, 2025, pp. 21 361–21 375.

[33] D. Han, J. Chen, Z. Guo, Q. Li, and B. Wang, “A novel exchange rate forecasting paradigm based on multi-agent collaboration and multimodal big data-driven methods,” *Big Data Mining and Analytics*, 2025.

[34] G. Chen, J. Yuan, J. Yao, Z. Luo, J. Li, and C. Luo, “Semi-supervised prefix tuning of large language models for industrial fault diagnosis with big data,” *Big Data Mining and Analytics*, vol. 8, no. 6, pp. 1353–1368, 2025.

[35] J. Zhou, R. Niu, B. Ji, Z. You, and X. Shang, “A knowledge graph enhanced pre-trained large language model for predicting microrna-circrna interactions,” *Big Data Mining and Analytics*, vol. 8, no. 6, pp. 1405–1417, 2025.

[36] C. Luo, J. Zhang, J. Guo, Y. Hong, Z. Chen, and S. Gu, “Energy efficiency maximization in riss-assisted uavs-based edge computing network using deep reinforcement learning,” *Big Data Mining and Analytics*, vol. 7, no. 4, pp. 1065–1083, 2024.

[37] C. Jin, T. Zhou, Y. Chen, K. Liu, and J. Zhao, “Maeps: Multi-agent event prediction system based on human expert team collaboration simulation,” *Tsinghua Science and Technology*, 2026.

[38] A. M. Sohail, Y. W. Teh, N. Khan, A. Koubaa *et al.*, “A comprehensive review: Analysis of machine learning, deep learning, and large language model techniques for revolutionizing driver identification,” *Tsinghua Science and Technology*, 2025.

[39] Y. Zhang, Y. Yu, X. Wang, X. Li, H. Liang, and P. Tiwari, “Multi-affection prompt learning for sentiment, emotion, and sarcasm joint detection in conversations,” *Tsinghua Science and Technology*, vol. 31, no. 3, pp. 1819–1837, 2026.

[40] G. Cai, R. Tian, L. Yang, Y. Jia, L. Li, and J. Wang, “Efficient inference for edge large language models: A survey,” *Tsinghua Science and Technology*, vol. 31, no. 3, pp. 1365–1380, 2026.

Author biography

Weiyue Chen received the B.S. degree in spatial information and digital technology from Xidian University, Xi’an, China, in 2024.

He is currently pursuing the M.S. degree with the School of Electronic Engineering, Xidian University, Xi’an, China. His current research interests include large language model powered agent collaboration.

Guoshuai Zhang received the B.S. degree in communication engineering from Changchun University, Changchun, China, in 2016, the M.S. degree in signal and information processing from SouthCentral Minzu University, Wuhan, China, in 2019, and the Ph.D. degree in electronic science and technology from Xidian University, Xi’an, China, in 2023. He is currently working as a Postdoctoral Researcher with Xidian University. His research interests include computational social science and autonomous agent.

Jiaji Wu received the B.S. degree in electrical engineering from Xidian University, Xi’an, China, in 1996, the M.S. degree astrometry and celestial mechanics from National Time Service Center, Chinese Academy of Sciences, Xi’an, China, in 2002, and the Ph.D. degree in electrical engineering from Xidian University, in 2005. He is currently a Professor with Xidian University. His research interests include hyperspectral/multispectral image processing, big data, Internet of Things (IoT), and high-performance computing.

Gwanggil Jeon received the B.S., M.S., and Ph.D. degrees from the Department of Electronics and Computer Engineering, Hanyang University, Seoul, South Korea, in 2003, 2005, and 2008, respectively. From 2009 to 2011, he was a Postdoctoral Fellow with the University of Ottawa, Ottawa, Canada, and an Assistant Professor with Niigata University, Niigata, Japan, from 2011 to 2012. He is currently a Professor with Incheon National University, Incheon, South Korea, and Xidian University, Xi’an, China. His research interests include image processing and computational intelligence. Dr. Jeon is an Associate Editor of Sustainable Cities and Society, IEEE ACCESS, Real-Time Image Processing, Journal of System Architecture, and Remote Sensing. His research interests include image processing and computational intelligence.