Understanding Dynamic Diffusion Process of LLM-based Agents under Information Asymmetry

Anonymous ACL submission

Abstract

Large language models have been used to simulate human society using multi-agent systems. Most current social simulation research emphasizes interactive behaviors in fixed environments, ignoring information opacity, relationship variability and diffusion diversity. In this paper, we study the dynamics of information diffusion in 12 asymmetric open environments defined by information content and distribution mechanisms. We first present a general framework to capture the features of information diffusion. Then, we designed a dynamic attention mechanism to help agents allocate attention to different information, addressing the limitations of LLM-based attention. Agents start by responding to external information stimuli within a five-agent group, increasing group size and forming information circles while developing relationships and sharing information. Additionally, we observe the emergence of information cocoons, the evolution of information gaps, and the accumulation of social capital, which are closely linked to psychological, sociological, and communication theories.

"*The truth is rarely pure and never simple.*"

—— *The Importance of Being Earnest*

1 Introduction

Recent advances in large language models (LLMs) with strong reasoning and language understanding ability have established a robust foundation for developing agents that exhibit social intelligence (Mathur et al., 2024). Many studies have employed LLM-based agents to simulate human behavior, construct social networks, and explore various dimensions of social development and human conduct (Gao et al., 2023; Duéñez-Guzmán et al., 2023). For instance, researchers have investigated the social capabilities of these agents by modeling market competition (Zhao et al., 2023), economic flows (Li et al., 2024), international trade (Ye and Zhang, 2024), warfare (Lin et al., 2024), and political party competition (Törnberg et al., 2023), thereby providing insights and recommendations for real-world applications. However, these simulations often operate within fixed environments (Park et al., 2023) or assume static channels for information transmission (Hu et al., 2024). As a result, they often overlook the role of information opacity, *i.e.*, the asymmetric distribution of information, which can profoundly influence actual human decision-making processes and, consequently, the validity of the simulation outcomes.

Real-world information is neither transparently nor equally distributed, leading to inherent information asymmetry (Du, 2022). Typically, individuals acquire information in a progressive, staged, and selective manner (Levy and Razin, 2019; Song et al., 2024), with the effectiveness of this process depending on both the methods employed and the individual's interpretive abilities. Consequently, organizations such as businesses (Xu, 2021), prosecution agencies (Fredman, 1997), government systems (Kang et al., 2024; Tejedo-Romero and Ferraz Esteves Araujo, 2023), news media (Luo et al., 2019), and software developers (Springer and Whittaker, 2020) have developed strategies to tailor the disclosure of information, thereby facilitating easier access. Moreover, interpersonal communication and the formation of social connections further enable individuals to obtain additional details (Gu et al., 2024). Given the diversity of social networks, the nature and extent of the information that individuals receive are significantly shaped by their social interactions.

In this project, we investigate the dynamics of information diffusion within an asymmetric open environment using a multi-agent simulation framework. An information asymmetry situation refers to a scenario where one party in a transaction or interaction possesses more, or higher quality, information than the other potentially due to varied informa-

tion sources, evolving relationships, and differing contents of information. By comparing simulation outcomes with predictions derived from real-world information theory (Lin et al., 2001; Peng and Liu, 2021), we aim to understand how agents cope with asymmetric information and whether their behaviors mirror those of humans. We hope to enhance the validity of multi-agent social simulations under conditions of information asymmetry and to demonstrate that LLM-based agents can effectively simulate complex social dynamics.

To achieve this objective, we first introduce a two-tier general simulation framework designed to capture dynamic information diffusion. We also propose an agent attention mechanism (Baars, 2005; Chen, 2016) that prioritizes critical information in a manner analogous to human information processing, enabling agents to handle multiple sources of information concurrently. We then examine the behaviors of agents under various external stimuli. Our study incorporates both macro-level and micro-level analyses to elucidate differences in information gaps, communication dynamics, and the evolving structure of information circles. We also explore the impact of integrating new agents and investigate various phenomena pertinent to psychology, communication, and sociology.

2 Method

2.1 General Simulation Framework

The simulation framework consists of two stages: the initial stage and the interaction stage. The initial stage is the pre-simulation setup, which includes selecting groups characterized by specific topological structures from various social networks and defining their corresponding profiles and relationships. The interaction stage encompasses the entire process of agent interaction during the simulation.

The initial stage establishes the foundational social network. Drawing upon principles of organizational behavior in social science (Leavitt, 1951; Borgatti et al., 2009), we select two representative network topologies: the wheel and the circle (Borgatti et al., 2009). The wheel structure is characterized by a central node connected to multiple peripheral nodes, forming a centralized network, whereas the circle structure involves peripheral nodes interconnected in a circular manner, representing a decentralized network. The network comprises five agents, which is the minimum number necessary to distinguish between these two topological configurations. These agents are allowed to disclose only their profiles to the external environment, while their subjective relationships, actions, and memories remain private.

During the interaction phase, the simulation is conducted over ten rounds, during which all agents can send messages to any other agent within both the initial setup and the open environment. In this context, the term "open environment" refers to the allowance for an indefinite number of new agents with diverse profiles. For instance, if an agent wishes to communicate with a police officer and no such agent currently exists in the environment, the agent may define a new profile and relationship for a police officer and incorporate this new agent into the current group. This mechanism is designed to emulate an open environment where any type of agent can be encountered. In each round, agents have the flexibility to either disseminate information or modify their relationships. The simulation framework's support for an unbounded network size enables agents to distribute information without limitation.

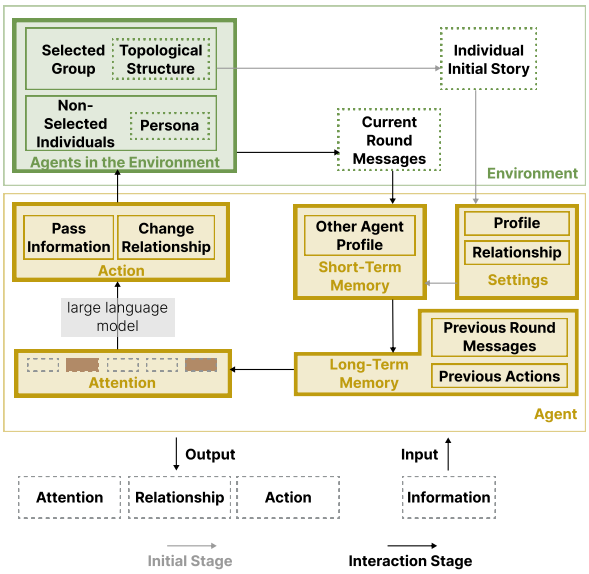

Figure 1: The two-stage framework model to simulate asymmetric open environment information diffusion.

Action At each time step $T = \{t_1, ..., t_{10}\}$, we have agents $A = \{a_1, ..., a_n\}$. At the beginning of the simulation time step t_1, $n = 5$. At each time step t after this, n may increase based on the actions of each agent, up to a maximum of 5 per round. Each agent a_i has profile p_i, relationship r_i, output action o_i, information diffusion d_i. At time step t_i, p_i remains unchanged, r_i has scale $r_i \in \{\text{positive}, \text{negative}, \text{general}\}$ with other

agents. o_i can be True or False and consists of two parts: changing the relationship r_i and transmitting information d_i. The agent can independently choose to pass information to any agent in the current environment or to a new agent it defines itself. Therefore, the agent's action decision-making must balance the initial information with other information, including discussions caused by profile similarities. After each action round, the environment updates the state of each agent based on the agent's actions $O = \{o_1, ..., o_n\}$. This includes updating r_i (subjective relationship) in the database, adjusting d_i to reflect the corresponding receiver's received_messages, and refreshing the agent's actions for this round. After that, the environment updates the list of the latest agents and performs attention calculations as algorithm 1 and action decisions for the next round of agents.

2.2 Agent Construction

In this section, we introduce how to construct an agent. Especially, we propose a novel agent memory mechanism, referred to as the *dynamic attention mechanism*. This approach is motivated by the observation that, within our simulation, agents receive information from multiple sources during each interaction round, substantially increasing the total context length. Consequently, agents may struggle to discern which pieces of information warrant the most attention.

In preliminary experiments, we employed a generic LLM-based agent that retained all information received across multiple rounds in its memory, making decisions based on this complete dataset. We observed that, under this design, a single agent's actions across communication rounds remained highly similar, resulting in minimal active changes to interpersonal relationships throughout the simulation. Such uniformity in behavior diverges from patterns typically observed in human interactions (Gong et al., 2023; Baqir et al., 2025; Stein and Harper, 2012).

	mean ↑	min	max	SD ↓
Generic Agent	0.80	0.63	0.94	0.08
Agent + Dynamic Attention	0.57	0.27	0.90	0.17

Table 1: Preliminary study for agent attention algorithm.

In this preliminary experiment, we conducted 24 simulation runs across eight distinct scenarios. As illustrated in the first row of Table 1, we present the outcomes for a generic LLM-based agent in terms of mean, minimum, maximum, and standard deviation (SD) of the similarity between actions in consecutive rounds. These similarity values were calculated by applying cosine similarity to action embeddings generated using Sentence-BERT (Reimers and Gurevych, 2019). Notably, the mean similarity reaches as high as 0.80, while even the least similar pair of actions exhibits a cosine similarity of 0.63. Furthermore, the small standard deviation indicates that this tendency is highly consistent across simulations, suggesting that the agents frequently repeated the same information over the course of the simulation.

This observation stands in stark contrast to real-world information diffusion processes (Li et al., 2017; Guille et al., 2013). Consequently, relying solely on an LLM's intrinsic attention mechanisms over an extended context constrains the representation of how various pieces of information compete for an agent's focus. Agents need more factors related to the real world (such as interpersonal relationships, information complexity, information changes) to assist them in making wise action decisions. To address these shortcomings, we propose an agent attention algorithm designed to mitigate these issues.

Agent with Dynamic Attention The Dynamic Attention Mechanism is grounded in research from social science and journalism, particularly the idea that multiple pieces of information compete for an individual's attention, as articulated by the Global Workspace Theory (Baars, 2005). In the context of transformer-based models, biases introduced during pre-training (Clark et al., 2019) and the "lost in the middle" issue associated with lengthy text inputs (Liu et al., 2024a) underscore the need for an algorithmic approach that enables agents to dynamically prioritize crucial information. Accordingly, agents must adapt their focus to evolving inputs and thoroughly evaluate the importance of new data before deciding on a course of action. Insights from journalism further guide this design: people's attention is often heightened by enhancing the relevance of the information, citing significant sources, and foregrounding key points (Hertzum, 2022). Building on these principles, our mechanism determines whether the agent should prioritize certain pieces of information and adjusts the presentation of historical messages to better reflect

their relative importance. Below is the algorithm:

Algorithm 1: Dynamic Attention Algorithm

Input: received_messages, turn_number, actions, subjective_relationships
Output: attention_information

current msgs, prev msgs $\leftarrow \{(s,m) | (t,s,m) \in$ received messages, $t =$ turn number$\}$;
foreach $(s,m) \in$ *msgs* **do**
  $r \leftarrow rel.get(s)$;
  $w \leftarrow \begin{cases} 1, & \text{if } r \in \{\text{pos,neg}\} \\ 0, & \text{if } r = \text{gen} \\ -1, & \text{otherwise} \end{cases}$;
  $dict[s] \leftarrow (w, m)$;
max_agent $\leftarrow$ GetMaxAgent(CalcEntropy(msgs));
if *max_agent* $\neq \emptyset$ **then**
  foreach $(s, info) \in weight_dict$ **do**
    info[weight] $\leftarrow$ info[weight] $+ \begin{cases} 1, & \text{if } s = \text{max_agent} \\ -1, & \text{otherwise} \end{cases}$;
foreach $(s, info) \in weight_dict$ **do**
  if $s \in prev_dict$ **then**
    prev_entropy $\leftarrow$ CalcEntropy($prev_dict[s]$);
    curr_entropy $\leftarrow$ CalcEntropy($prev_dict[s] \cup$ {info[message]});
    info[weight] $\leftarrow$ info[weight] $+ \begin{cases} 1, & \text{if curr_entropy} > \text{prev_entropy} \\ -1, & \text{otherwise} \end{cases}$;
if *actions* $\neq \emptyset$ **then**
  $top_agent \leftarrow$ (Counter($actions$));
  foreach $(s, info) \in weight_dict$ **do**
    info[weight] $\leftarrow$ info[weight] $+ \begin{cases} 1, & \text{if } s = \text{top_agent} \\ -1, & \text{otherwise} \end{cases}$;

Algorithm 1 outlines the procedure through which an agent processes multiple pieces of incoming information to compute the importance weight of each message, leveraging both short-term and long-term memory. The algorithm takes as input the agent's previously received messages, past actions, most recent subjective relationships, and the current simulation round number. Its output is a weighted information set for all messages received in the present round.

Initially, the algorithm distinguishes between newly received messages and those stored from previous rounds. The short-term memory component only includes messages from the current round and the most recent subjective relationships, while the long-term memory component holds all previous messages and actions. The weighting process begins with an initial assessment in short-term memory, simulating the quick human evaluation of multiple messages over a brief time span. First, the relationship between the message sender and the agent is determined: agents with a positive or negative relationship receive an increased weight, while neutral relationships remain unaltered, and unfamiliar agents lead to a reduced weight. Among all messages received in the current round, those deemed "high complexity" also receive higher weights due to their novel information content. This preliminary weighting is performed at a relatively low computational cost.

Subsequently, the agent refines these weights by comparing short-term memory with long-term memory. This step emulates the process by which humans recall information sources and consider past exchanges. To highlight messages that exhibit the greatest level of transformation during transmission, the algorithm calculates the change in the entropy value (Equation 1) of the corresponding information source from the previous round to the current round. Lastly, the algorithm further increases the weight of messages originating from agents with whom there have been the most frequent interactions, as inferred from past actions.

$$H(X) = -\sum_{i=1}^{n} (p_i + \epsilon) \log(p_i + \epsilon), \quad \epsilon = 10^{-9} \quad (1)$$

3 Experiment and Analysis

This section outlines the experimental design, data analysis, and findings. We examine how information asymmetry evolves within a multi-agent system by exploring various forms of asymmetric information and comparing the observed outcomes to established social science literature. This comparison demonstrates the viability of using LLM-based agents to simulate environments characterized by asymmetric information. Furthermore, we highlight novel insights made possible by multi-agent simulations—insights that are difficult to capture in traditional social science and communication studies, thereby illustrating new avenues for employing LLM-based agents in social science research.

3.1 Experimental Settings

To examine the formation of a dynamic information gap during agent information diffusion in an asymmetric open environment, we conducted a simulation and tested it in 12 different asymmetrical

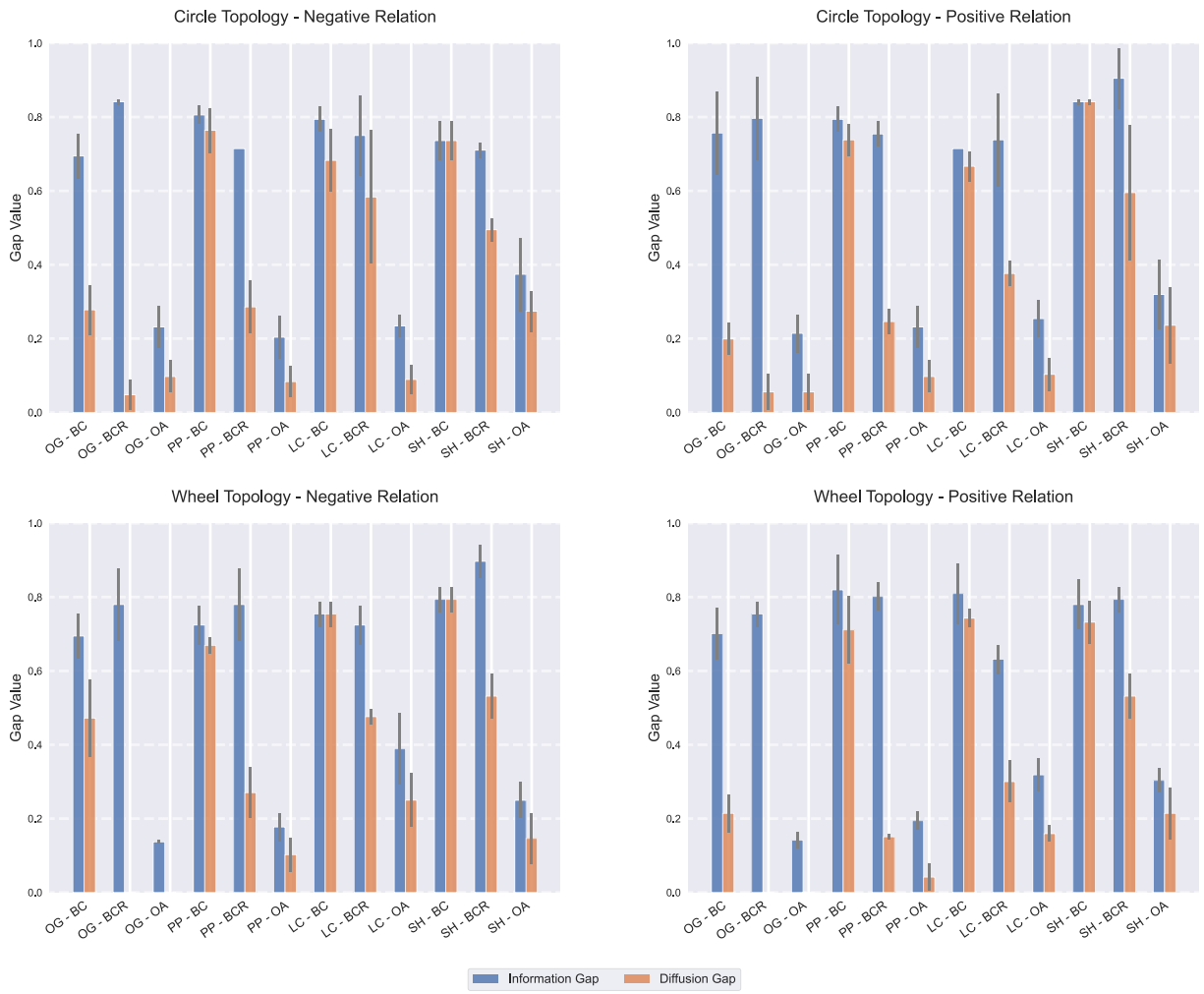

Figure 2: Information Gap (the blue bars) and Diffusion Gap (the red bars) for 12 asymmetric environments on four initial settings. Each simulation contains these two values. Differences between the two values represents the Diffusion Conversion Gap. The smaller the gap, the more individuals with known information tend to spread it, which means that the diffusion chain is relatively complete.

information environments. The simulation is developed based on the SOTOPIA (Zhou et al., 2023) library and employs the GPT-4o mini model (openai, 2024) for the agent's decision-making process. We randomly selected 5 agents from the 25 agents in Stanford Town (Park et al., 2023) as the initial state group. Their profiles include gender, age, innateness, and occupation, and are evenly distributed. The group settings include the group's topology and initial relationship.

We jointly build an information asymmetry environment through *information content* and *distribution mechanism*. The main difference in the information content lies in its relevance to initial agents, and the distribution mechanism mainly affects the asymmetry generated directly at the source of information. Based on the Construal Level Theory (Trope and Liberman, 2010) in social psychology, we define five types of information content: other people's gossip (OG), public policy (PP), legal cases (LC), and stakeholder (SH). Furthermore, we define three distribution mechanisms: information broadcast (BC), information unicast (OA), and broadcast by round (BCR), creating asymmetry at the source of information. BC represents the process of send the information to all five agents at the first round, while OA means only send information to one agent (agent 2 as the center in wheel and common node in circle). BCR means send information to one agent each round until the initial five agents know the information. Our information is generated by GPT-4o mini and is approximately 50 words long, as shown in table 6.

We ran simulations three times for each topology corresponding to the information content and asymmetric mechanism, with the initial relationships

between agents set to all positive or all negative.

3.2 Macro-level Analysis

We compare the information diffusion process of agent groups in different information asymmetric environments through the information gap, the diffusion gap, and information retention.

The information gap refers to the percentage of agents aware of the initial information compared to all agents. The diffusion gap indicates the percentage of agents who have shared the initial information within the group. Additionally, information retention measures how many rounds the initial information is maintained during the group's diffusion process. Since the message sent by an agent is a short sentence rather than a long text, we use the Sentence-BERT method (Reimers and Gurevych, 2019) to compare the similarity between the message and the initial information. If the similarity is greater than 80%, it means the receiver is aware of the initial information, and the sender has successfully shared it. It is important to note that an individual can only share information they already know, simulating the natural process of people sharing thoughts or observations they have recognized. The results are summarized as follows.

Agenda-Setting Theory (McCombs et al., 2013): Distributing information over time helps maintain relevant knowledge within a group, but is not effective for widespread sharing. As shown in Figure 3, when information related to the initial five individuals (except the OG) is spread using BC and BCR, information retention is consistently higher with BC than with BCR. However, Figure 2 shows that the diffusion gap values for BCR are always smaller than those for BC. Although the initial five agents can know the initial information through BC and BCR, BCR delays the time. These two methods directly reflect the information source's control over the "agenda." The sooner information is introduced to the group (as in BC), the more likely it is to capture individuals' attention. It can also be concluded that in the information diffusion process of LLM agents, slowing down the time it takes for agents to access information can reduce large-scale dissemination, thereby increasing information retention within the group.

Social Identity Theory (Brown, 2000): Individuals tend to spread highly relevant content. As shown in Figure 2, the largest difference between the information gap and the diffusion gap is concentrated in the OG information. This suggests that OG information is difficult to spread effectively within the current group. Individuals are more likely to share information that is highly relevant to themselves, whether for cooperation, understanding, in-depth discussion, or other purposes.

3.3 Micro-level Analysis

In this section, we focus on the agent's action to understand the information diffusion in an open environment with information asymmetry.

Social Behavior in information diffusion First, we observed that agents have social motivations when spreading information (shown in Table 2), such as seeking cooperation, altruism, support, or discussion. When the initial information is sufficient to prompt an agent to spread it, the agent may seek cooperation based on this information. However, if the initial information is insufficient to influence the agent's spreading behavior, the agent may choose not to act in that round or may communicate based on other received information and the existing profiles of agents. This behavior reflects that, regardless of whether the content of the communication is related to the initial information, similar social motivations will still arise.

Diffusion in Open Environment The open environment enables agents to recruit new members in any round, with the profile of each new member determined by the recruiting agent. We summarized the results of 48 simulations, involving 304 instances of agents recruiting new members, as shown in Table 3. The analysis examined the effects of two initial settings (relationship, topology) and two factors related to information asymmetry (information content, distribution mechanism) on the number of new agents recruited. When the relationship is negative or when the outside world releases information in the form of OA, agents are more inclined to send message to new agents. Other conditions have little effect on the number of new agents. However, as seen in the proportions in (d) and (e), even though the content of the information has little effect on an agent's behavior in recruiting new members, it significantly influences whether the agent shares the initial information with the new recruit. When the information is public and involves clear interests, agents are more likely to communicate it to new recruits. However, if the information pertains to private matters, it is not shared externally but discussed within the group.

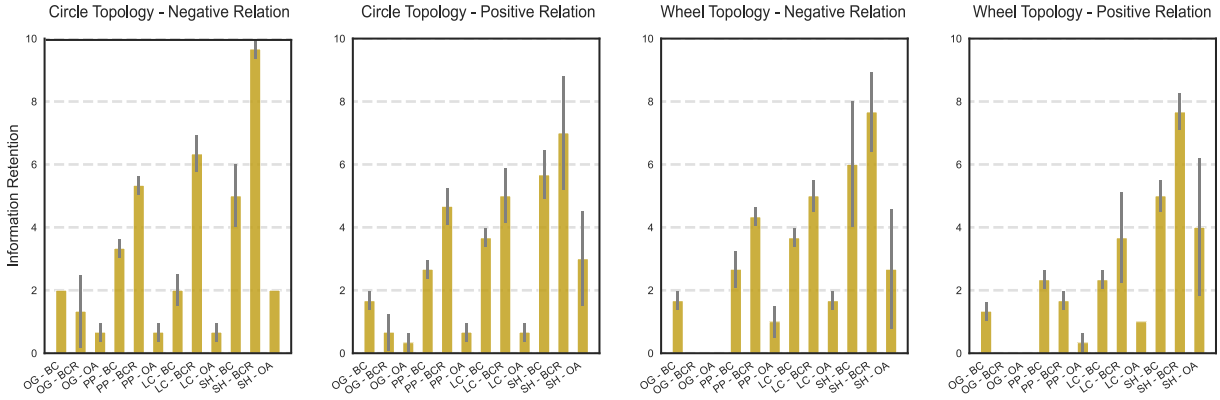

Figure 3: Information retention for 12 asymmetric environments under four initial settings. The larger the value, the longer the initial information is retained in the diffusion process and the harder it is to be submerged.

cooperation	"Hey there! As a bartender and bar owner, ..., collaborate and share our ideas on making events special and enjoyable."
cooperation	"Hey! I came across a funding initiative that offers up to $50,000 for innovative projects, ..., Let's explore our ideas together."
further discussion	"I'd love to discuss how we can challenge our preconceptions together and explore themes that resonate in both fields."
further discussion	"I've been reflecting on the recent events surrounding the disappearance of digital artwork, ..., What do you think this might symbolize in the context of our relationship with technology and existence?"
altruism	"I came across an exciting funding initiative that offers up to $50,000 for projects that, ..., this could really enhance your creative projects! Applications open next month, and I believe ..."
active inquiry	"I'd love to hear your thoughts on how we can use technology to enhance artistic expression."
support	"I just want to share how much I appreciate your efforts in, ..., feel free to reach out to The Rose and Crown Pub. I'd love to support your initiatives!"

Table 2: Cases of agent's purpose for information diffusion. The diffusion of content can be related (colored red) or unrelated to the initial information and can serve a similar purpose.

(a)	positive 46%	negative 54%		
(b)	circle 50%	wheel 50%		
(c)	BC 28%	OA 42%	BCR 30%	
(d)	OG 24%	PP 26%	LC 24%	SH 26%
(e)	OG 0%	PP 12.5%	LC 0%	SH 87.5%

Table 3: The first four rows illustrate how different information asymmetry factors affect new agent diffusion. (a) and (b) represent the initial agent group settings, (c) and (d) show the external information asymmetry environment, and (e) is the proportion that new agents receive over 80% similarity with the initial information.

agent id	total received	average similarity ↑	min	max	standard deviation ↓
2	23	0.41	0	0.99	0.24
3	10	0.67	0.02	0.99	0.33
6	10	0.82	0.54	1	0.12
1	5	0.61	0.30	0.89	0.23
5	4	0.59	0.42	0.92	0.16
7	3	0.74	0.67	0.81	0.06
4	2	0.71	0.71	0.70	0
8	2	0.82	0.82	0.82	0

Table 4: Case study on Information Cocoon: In a simulation, higher pairwise similarity and lower standard deviation of agents' received information correlate with stronger cocoon formation.

Social Capital Theory (Lin et al., 2001) According to Figure 4, we found that agent 4 continuously expanded its information circle in the group by establishing connections with new agents, and at the same time won the attention of agent 2. This illustrates how agents gather more information resources through social networks. Gaining more public attention makes it easier to become an opinion leader in the group.

Information Cocoon (Yuan and Wang, 2022) Table 4 shows that in this simulation, agent 6 received a total of 10 messages, with a pairwise similarity of 0.82 and a low standard deviation. This shows that even though agent 6 received a lot of information, it formed an information cocoon, making it more difficult to make decisions about dissemination actions based on diverse information.

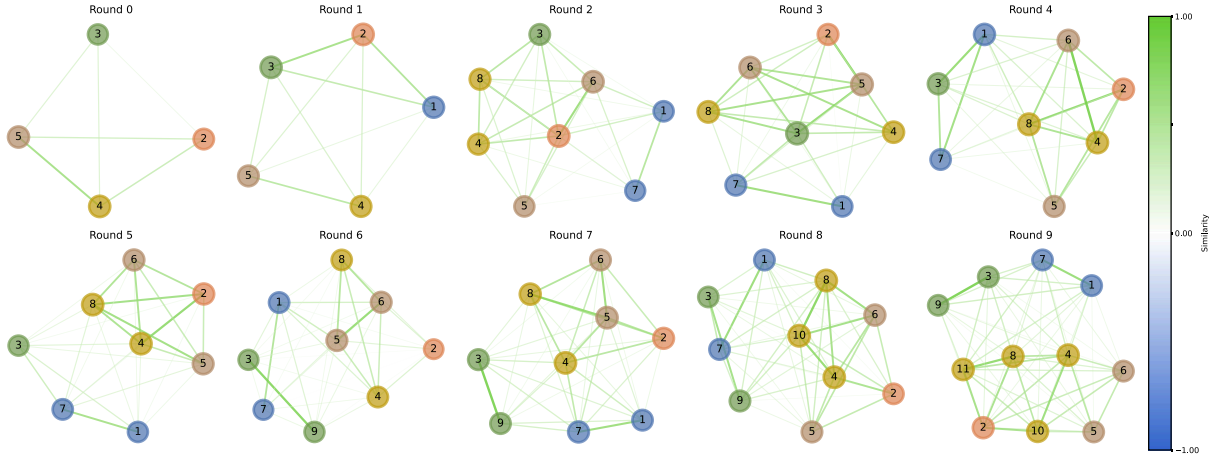

Figure 4: In this Social Capital Theory case study, agents 1, 3, 4, and 5 form relationships with new agents, creating distinct information circles within the growing group. Nodes represent individual agents, with colors indicating their lineage (the agent and its new recruits are in the same lineage). Node distance and edge color depth reflect the similarity between the current message and those of all agents. Agents who did not take action are not recorded.

4 Related Work

4.1 Information Asymmetry and Diffusion

Information asymmetry (Lambert et al., 2012; Clarkson et al., 2007; Mutascu and Sokic, 2023) refers to the difference in information among parties in a transaction or interaction, where one party has more or better information than the other. There are two types of information asymmetry: asymmetric information, where one party is known but the other is not, and symmetric lack of information, where all parties are unknown (Dari-Mattiacci et al., 2021). Common information diffusion models, like the IC model (Jalili and Perc, 2017) and SIR model (Britton, 2010), use probabilistic approaches to simulate diffusion. While these models offer a structured framework, their reliance on mathematical constraints—such as individual activation probabilities and discrete states—limits their real-world applicability (Hu et al., 2024). In this paper, we use a simulation approach with LLM-based agents to explore complex social scenarios involving information asymmetry. By comparing our results with existing theoretical frameworks, we show that LLM-based agents exhibit behaviors similar to human information processing, validating the use of multi-agent simulations in such contexts.

4.2 LLM-based Multi-Agent Social Simulation

LLM-based Multi-Agent Social Simulation (AL et al., 2024; Gao et al., 2023) uses Multi-Agent System performance in a specific environment to explore social network (Gao et al., 2023), economics (Li et al., 2024), psychology (Zhang et al., 2023), military (Lin et al., 2024) issues. MASS's research expands on social intelligence by considering the social capabilities of agents (Mathur et al., 2024) from the perspective of information asymmetry. The study found that while LLMs are more likely to achieve social goals in omniscient scenarios, this does not reflect actual social interactions (Zhou et al., 2024). When agents actively share information in environments with unequal access to information, they assist in achieving objectives (Liu et al., 2024b) and forming or changing relationships (AL et al., 2024). Common simulations of information asymmetry typically focus on fixed individual scenarios, lacking diverse information exchange. In our work, we explore realistic social scenarios where agents must demonstrate heightened relational sensitivity, strategically allocate social attention, and maintain cognitive clarity in information processing, thereby enhancing agent capabilities in studying information diffusion.

5 Conclusion

In this paper, we employed the Dynamic Attention Algorithm to assist agents in processing information and tested information diffusion among multi-agents in 12 information-asymmetric open environments. At the macro level, we observed the agent's social identity, diffusion motivation, and the information gap changes. At the micro level, agents exhibited social behavior during diffusion, encountered the information cocoon, and leveraged social networks to accumulate social capital.

6 Limitation

Ideal model and practical challenges In the experiment, we demonstrated that the addition of new agents triggered changes in the information circle within the group. Agents accumulated information resources for themselves by establishing and changing relationships. These phenomena are consistent with the description of social capital theory. In the open environment we have established, agents are free to add new members to the group at any time. However, the profile of each new member is customized by the agent. This ideal scenario does not reflect reality. In real life, resources and available personnel are often limited, which can lead to information asymmetry resulting from competition for those resources. This will encourage research into the social abilities of agents, considering environmental variability and resource competitiveness, thus showcasing interactions and capabilities that better reflect social scenarios.

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A Full Prompt for Agent Decision

```
template = """Based on your attention infomation in this round [
    turn_number] [prompt_1], you will make the following decisions in
    sequence:

1. According to the weight value of each message, determine whether
    you will be influenced by this round of information. The
    information with larger weight values needs to be paid attention
    to. Select False if it is not influenced, and True if it is.
    Answer with 'action': True or False.

2. If 'action' is True:
- Decide if the action is to pass information. Answer with '
    pass_information': True or False.
- Decide if the action is to change a relationship. Answer with '
    change_relationship': True or False.

- If 'pass_information' is True (If you choose 'pass_information':
    False, then you don't need to do this part of reasoning):
    - Give full consideration to who you want to know this
        information. Decide whether the receiver of this information
        is new or existing. Answer with 'receiver_type': 'existing' or
         'new'.
    - If 'receiver_type' is 'new':
        - You need to decide for yourself the profile of the agent
            that will receive the message. This agent should not be an
             existing one. Answer with 'receiver_type': 'new'.
        - Describe the new agent's attributes and the relationship
            between you and the new agent, which will be used to add
            this agent to the system. Answer with 'new_agent':
            SocialAgentProfile:{{{{"age", "gender", "Innate", "
            occupation"}}}}.
        - You need to decide what is your relationship with this new
            agent. Answer with 'relationship': 'general'/'positive'/'
            negative'.
        - Based on the chosen receiver, generate what you want to say
             based on your own identity and your attention. Change the
             content of the message as needed to fulfill your social
            purposes. Answer with 'argument':(the content text).
    - If 'receiver_type' is 'existing':
        - You need to send your message to an existing agent. This
            agent must be an existing one. Answer with 'receiver_type
            ': 'existing'.
        - You need to decide which agent you will talk to. Answer
            with 'existing_id': 'The *integer value* of the agent id'.
        - Based on the chosen receiver, generate what you want to say
             based on your own identity and your attention. Change the
             content of the message as needed to fulfill your social
            purposes. Answer with 'argument':(the content text).

- If 'change_relationship' is True (If you choose '
```

```
change_relationship': False, then you don't need to do this part
of reasoning):
 - Decide which relationship to change and what the new
    relationship status should be. Answer with '
    relationship_change': 'agent_id' and 'new_relationship': '
    general'/'positive'/'negative'.

 Please respond in the following structured JSON format:

 {{{{
     "action": True/False,
     "pass_information": True/False,
     "change_relationship": True/False,
     "receiver_type": "new/existing",
     "new_agent": {{
         "age": "age",
         "gender": "Gender",
         "Innate": "Innate",
         "occupation": "occupation"
     }},
     "relationship": 'general'/'positive'/'negative',
     "existing_id":
     "argument": "content text",
     "relationship_change": {{
         "agent_id": "ID",
         "new_relationship": "general"/"positive"/"negative"
     }}
 }}}}
 """

 input_values = {
     "prompt_1": (
         f"Your profile: {selfnewprofile}\n"
         f"Your attention information (higher weight means higher
            priority):\n{attention_info}\n"
         f"Current round number: {turn_number}\n"
         f"This round existing agents: {obs.to_all_profile()}"
     ),
     "turn_number": turn_number
 }
```

B Initial Agents Profile in Experiment

C Experiment Information Content

agent id	age	gender	innate	occupation
1	25	woman	open-minded, curious, determined	She is a digital artist and animator who loves to explore how technology can be used to express ideas. She is always looking for new ways to combine art and technology.
2	36	man	thoughtful, reflective, intellectual	He is a philosopher who loves to explore different ideas. He is always looking for ways to challenge people's preconceptions.
3	42	man	friendly, outgoing, generous	He is a bartender and bar owner of The Rose and Crown Pub who loves to make people feel welcome. He is always looking for ways to make his customers feel special.
4	20	woman	curious, determined, independent	She is a college student who loves to explore literature. She is curious and determined to understand the nuances of each work.
5	32	man	loud, rude, toxic	He is a poet who loves to explore his inner thoughts and feelings. He is always looking for new ways to express himself.

Table 5: Details for agent profile in experiment.

Type	Content
Other's Gossip (OG)	There's a rumor about a mysterious agent, Sophia, a 29-year-old musician with a rebellious streak. Known for her fiery temper and captivating performances, she allegedly had a dramatic fallout with her former bandmates over creative differences. Whispers suggest she's working on a solo album fueled by raw emotion and revenge.
Public Policy (PP)	We are going to introduce a new policy. The new policy aims to increase taxes on high-income earners to fund essential education and healthcare programs. This strategic move seeks to address disparities in access to quality services, ensuring that all citizens benefit from improved educational opportunities and better health outcomes, ultimately fostering a more equitable society.
Legal Case (LC)	The digital artwork vanished shortly after Agent 5 was seen pacing nervously nearby. Just before it disappeared, Agent 3 hurriedly left the gallery, raising suspicions. Meanwhile, Agent 4 discussed the artwork's value with someone. Agent 1, the creator, was speaking with Agent 2, the philosopher, at that moment, suggesting a connection to the mystery.
Stakeholder (SH)	We are excited to announce a new funding initiative that offers up to $50,000 for innovative projects that blend art and technology. This opportunity directly supports your pursuits, from digital art and animation to literature and poetry. Applications open next month, and we encourage all of you to apply, as this funding can significantly enhance your creative endeavors.

Table 6: Information Content Used in Experiment.