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Interplay between Information and Behavior Based on Small Group Effect on Multilayer Social Networks

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Abstract

In the era of big data, massive amounts of information play an important role in individual behavior and decision-making. In order to investigate the interaction mechanism between information and individual behavior, we consider the influence of the "small group" network structure in social networks, and construct an information-behavior coupled dynamics propagation model (UAL-NBN) based on small group effect. Then we carry out theoretical analysis and derive the dynamic evolution equations for the model used the Micro Markov Chain Approach (MMCA). And we verify the correctness of the theoretical analysis by performing Monte Carlo simulations (MC). The results show that the small group effect does promote the spread of information and behavior in the population, which is reflected in reducing the epidemic threshold and increasing the outbreak size. In addition, we also conclude that the more small group structures exist in social networks, the more significant the promotion effect of the small group effect is. Finally, we describe the specific application of the model in scenarios such as epidemic control, rumor governance, social behavior advocacy, and consumer marketing, and provide theoretical reference and suggestions for the government and other relevant departments to formulate policies which promote the spread of behavior in society through information dissemination.

Keywords: Small group effect, information dissemination, social behavior diffusion, multi-layer social network.

1 Introduction

The development of the Internet and new media and the advent of the 5G era have changed people's social habits. Online social networks have become the main platform for people to exchange ideas, share information and transfer knowledge, which makes information flow faster and wider [1]. According to the Global Digital Report released by Hootsuite and We Are Social in April 2022, there are 5 billion Internet users worldwide, accounting for 63% of the world's population; among them, 326 million new social media users were added in the past year, which is an increase of 7.5 percentage points from the previous year; and these users use an average of 7.4 social platforms per month and spend an average of 2 hours and 29 minutes on social networks every day, which is 7 minutes longer than usual [2]. The massive amount of information that users encounter on social media every day plays an increasingly important role in people's lives, affecting people's behavior and decision-making [3–8]. Therefore, trying to understand the inner mechanism by which information affects people's behavior and decision-making can help us to better utilize the dividends brought by the information society.

In recent years, many scholars have devoted themselves to studying the interaction between information and behavior. The study found that information diffusion can promote the spread of social behavior, and at the same time, social contagion can also enhance the process of information diffusion [9, 10]. Literature [11, 12] used multiple networks to study the propagation mechanism of green behavior under the influence of awareness and the impact of negative information dissemination on the adoption of green behavior. The results showed that the formation of people's green consensus is closely related to the dissemination of green information, and the dissemination of green information in turn promotes the adoption of green behaviors. Literature [13] pointed out that in the process of innovation diffusion, individuals make adoption decisions based on the information they have obtained, and the influence of information transfer between individuals on innovation adoption behavior is particularly important. Literature [14] proposed an optimal strategy model for epidemics by considering interactions between individuals and the impact of online emotional information on human behavior, striving to minimize the infection burden on the health care system and the financial loss of economic activity during the lockdown.

Moreover, in the field of epidemiology, the impact of information dissemination on the spread of epidemics has also attracted the attention of scholars [15–17]. Literature [18] superimposed the SIS model of information dissemination with the SIRS model of epidemiology to study the interaction between local behavioral responses and endemic diseases. Literature [19] explained the impact of information on appropriate precautions on individual behavioral responses. Literature [20] found that the spread of awareness can induce informed individuals to take action to prevent infection, thereby affecting the infection threshold and transmission process of epidemics. Literature [21] pointed out that the purpose of reducing disease can be achieved by controlling the dissemination of information awareness at the information layer and the individual behavior at the other layer. Literature [22] found that information awareness about epidemics spread through multiple channels can reduce the infection rate by stimulating individuals to take vaccination behaviors, and awareness spread through various information sources is positively correlated with epidemic containment. As above, previous studies have demonstrated that information transmitted in the population can guide individuals to adopt protective behavioral responses, thereby reducing the risk of infection in the population and containing the spread of the epidemic [23–28].

In addition, the development of complex networks has provided new insights into the study of spreading dynamics [29, 30]. Initially researchers developed studies based on single layer networks, however, in reality many natural and artificial complex systems are coupled together through multiple types of interactions [31]. Therefore, researchers have started to use multilayer networks as a basic tool to quantitatively describe the interactions among multiple components in complex systems [27, 32, 33]. They abstract natural and artificial complex systems (e.g., communication networks, transportation networks, biological networks, etc.) into complex networks, where nodes represent individuals or entities, intra-layer connected edges represent interactions between nodes of the same layer, and inter-layer connected edges represent coupling relationships between nodes of different layers [34], which may lead to results beyond what can be captured by a single-layer network [35]. Based on multilayer networks, researchers have in turn conducted a number of meaningful studies on spreading dynamics over complex networks from multiple perspectives, including network structure [36], immunization strategies [37], and demographics [38]. Among them, understanding the specific network topology is fundamental to understanding the function and behavior of complex systems [39, 40]. Literature [41] explored the interaction of coupled propagation dynamics by constructing a composite network containing community structures. The results showed that promoting the spread of information is beneficial to suppressing the spread of disease, but changing the process of disease spread has no significant effect on the spread of information. And reducing long-distance jumps can also help slow the spread of the epidemic. Through theoretical analysis and computer simulation, literature [42] found that the influence of information layer heterogeneity on the epidemic threshold is closely related to the probability of information dissemination. When the information dissemination rate is low, strong heterogeneity can effectively improve the epidemic threshold; when the information dissemination rate is high, the opposite is true; when the information dissemination rate is neither too high nor too low, weak heterogeneity of the information layer can effectively suppress the spread of epidemics. Literature [43] proposed a new epidemic model considering partial mapping relationship based on time-varying network, and confirmed that the corresponding ratio between two layers of nodes has a significant impact on the epidemic threshold of the proposed model. In addition, many scholars have studied and verified the influence of network degree distribution on the scale of epidemic outbreaks [44–46].

To sum up, network structures like the degree distribution can, to a certain extent, facilitate or inhibit the propagation process in the population [47]. However, these related studies are based on pairwise interactions between nodes; in fact, people are always more inclined to trust people they are familiar with [48, 49], and individuals tend to show herd behavior in the decision-making process [50–53]. Thus, interactions may often occur in clusters of three or more nodes and cannot be described simply by pairwise interactions between two nodes [54]. For example, in social networks, rumors that are shared by multiple friends are more likely to be accepted by individuals, and individuals can also pass on rumors to multiple friends at the same time [55]. So considering the group effect produced by the "small group" structure composed of strongly connected neighbors will make the propagation process more realistic. However, few studies have taken into account the influence of the "small group" structure existing in the information dissemination network and the behavior diffusion network on spreading dynamics, that is, the influence of the group effect composed of strongly connected neighbors on the propagation process. Therefore, we provide a general research framework for information-behavior coupled systems based on multi-layer networks, and then consider the influence of the "small group" structure existing in the population on the information-behavior coupling dynamics. This can fill the gaps in the literature in this area, and can also provide theoretical reference and policy recommendations for the prevalence of behavior in society at the information level.

The rest of this paper is organized as follows: Section 2 introduces the construction process of the information-behavior coupled network model affected by the small group effect in detail. Section 3 uses the MMCA method to analyze the model theoretically. Section 4 analyzes the influence of the parameters of the model on the dynamic process; Section 5 discusses the scenarios in which our model can be applied, as well as the existing limitations and future work.

2 Models and Methods

2.1 Construction of Information-Behavior Coupling Network Model Framework

In order to analyze the interaction between the two dynamic processes of information diffusion and behavioral diffusion, and to further explore the influence of "small group effect" on the whole system, we establish a two-layered information-behavior coupled dynamic propagation model under the framework of multiple networks as shown in Figure 1. The upper network is the information dissemination layer, and the lower network is the behavior diffusion layer. The two networks have the same number of nodes but different topological structures. The links in the information dissemination layer represent all the ways people can receive information online or offline, and the links in the behavior diffusion layer represent all the ways people can contact and observe the behavior of others offline. It is worth noting that the links between the upper and lower layers overlap, but are not completely inclusive.

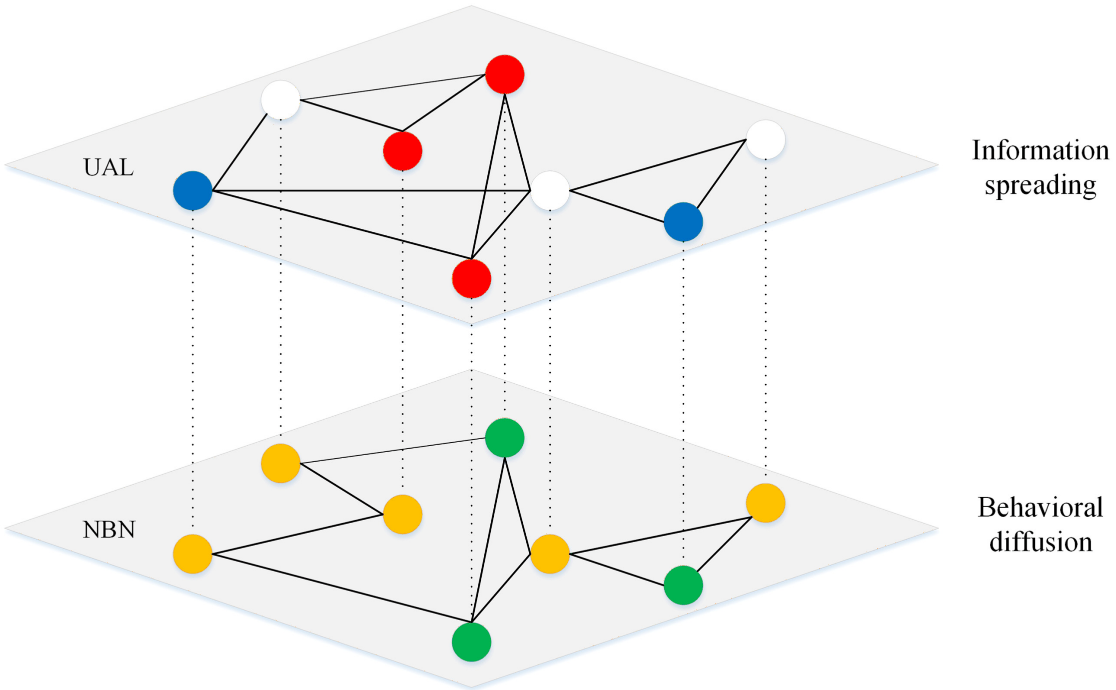


Figure 1: The framework of information-behavior coupling system based on multiple networks (UAL-NBN). The upper network describes the process of information dissemination. The nodes in this layer contain three states: U (white node), A (red node), and L (blue node). The lower layer network describes the process of behavior diffusion, and the nodes in this layer have only two states: N (yellow node) and B (green node).

Specifically, in the information dissemination layer, we use the unaware-aware-loss interest (UAL) model to model the process of information dissemination in the crowd. The three states of the node in this layer: U, A, L, respectively represent the three states of the node not knowing the relevant information, knowing the information and willing to spread the information, knowing the information but unwilling to spread the information. At time t, the node U that does not know the information will be informed of the information by the node A that knows the information and is willing to spread the information with the probability λ ; the node A that knows information and is willing to spread information will lose interest in the information with the probability δ and change to the L state, and no longer have the ability to spread information. In addition, in the information dissemination layer, if the conditions for the "small group effect" to take effect are satisfied between nodes, the node U that does not know the information increases the probability of λ^* to get the information from its neighbors in the same group. The state transition of the information dissemination layer is shown in Figure 2.

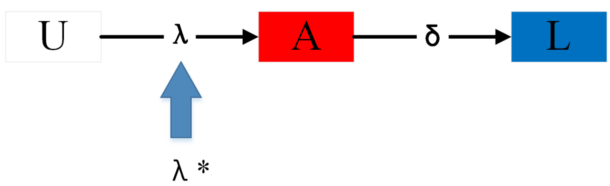


Figure 2: The state transition diagram of the UAL model in the information dissemination layer.

In the behavior diffusion layer, we use the non-behavior–behavior-non–behavior (NBN) model to describe the process of behavior diffusion in the population. The nodes in this layer contain two states N and B, which represent that the node does not adopt relevant behavior and adopts relevant behavior, respectively. At time t, the node N that does not adopt behavior will be affected by its neighbors that adopt behavior with probability β, and it will change to state B that adopts behavior. At the same time, the node B that adopts behavior will also change to state N with probability μ, and will no longer adopt this behavior. Moreover, in the behavior diffusion layer, if the conditions for the "small group effect" to take effect are also satisfied between nodes, the probability that a node N that does not adopt behavior is influenced by its group to change to state B that adopts behavior increases by β^*. The state transition diagram in the behavioral diffusion layer is shown in Figure 3.

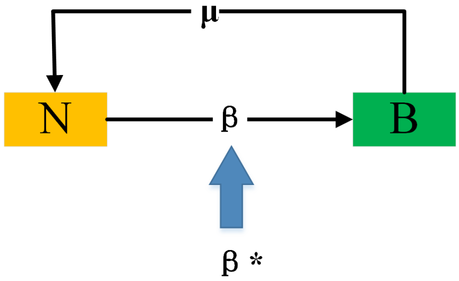


Figure 3: The state transition diagram of the NBN model in the behavioral diffusion layer.

In addition, there is a one-to-one correspondence between the nodes of the information dissemination layer and the behavior diffusion layer. The upper layer network acts on the lower layer network through the behavior enhancement factor $\sigma(0 < \sigma < 1)$, and the lower-layer network exerts a certain degree of influence on the upper-layer network through the shared interest $\omega(0 < \omega < 1)$ of the nodes. Specifically, if the node in the upper layer is in the A or L state with known information, the probability of the node being influenced by its neighbors in the behavior diffusion layer and adopting the behavior increases by σ, that is, $\beta^A = \beta^L = (1 + \sigma)\beta$; if the node in the lower layer is in the B state that adopt behavior, the node will immediately become the information-aware state in the information dissemination layer, but whether it changes to the A state that is willing to propagate or the L state that loses interest in information depends on personal shared interests ω. Therefore, we set that if the shared interest of a node is less than or equal to ω, the node changes to the A state that is aware and willing to spread; if the shared interest of the node is greater than ω, the node changes to the L state that knows the information but is unwilling to spread any more.

2.2 Construction of Information-Behavior Coupling Dynamics Propagation Model Based on Small Group Effect

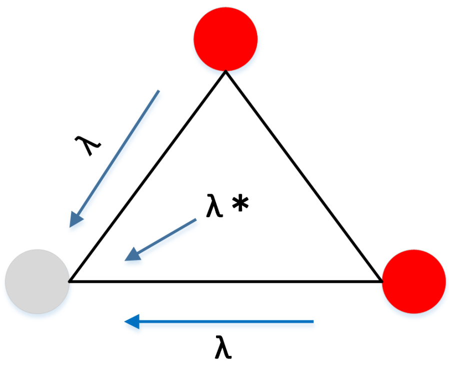
Large communities and their high-value effects are made up of countless smaller communities. Compared with large groups, users who are active in small groups are more easily influenced by their peers. In this paper, we refer to the phenomenon that people are active in small groups to share information and behavioral decisions to influence dissemination as the "small group effect". And then, we only consider the "small group" structure consisting of three individuals, and the individuals located in this structure know each other, trust each other, and have connections with each other.

First, we need to construct the "small group" structure for our proposed two-layered network model framework, which can be divided into the following two steps:

(1) Since the information dissemination layer simulates people's online + offline social circle, and the behavior diffusion layer simulates the life circle that people can reach offline, so initially, we construct a scale-free (SF) network for the information dissemination layer, of which the power exponent is α, and construct a small-world (WS) network for the behavioral diffusion layer that is connected to the k nearest neighbors with a reconnection probability p.

(2) Then we add the "small group" structure by traversing all the nodes in the network in turn. Taking node i in the information dissemination layer as an example, we take any two nodes j and l in its neighbors. If there is no connection path between node j and node l, we add a connection edge to it with probability p_1. Similarly, we add connecting edges to form the "small group" structure between nodes in the behavioral diffusion layer with probability p_2.

Next, we further define the conditions that make the "small group effect" work in the information dissemination layer and the behavior diffusion layer on the network with the "small group" structure. We assume that in a "small group" containing three individuals, the "small group effect" will only work when one and only one node is in the susceptible state and the other two nodes are in the infected state. At this time, the group will increase the probability of the only susceptible node in the small group being infected by the group effect factor γ. In other words, a small group consisting of one U node and two A nodes in the information dissemination layer can make the "small group effect " take effect (in this case, the role of the small group effect in the upper network is $\lambda^* = \gamma\lambda$, otherwise $\lambda^* = 0$); a small group consisting of an N node and two B nodes in the behavior diffusion layer can make the "small group effect" come into play (in this case, the role of the small group effect in the lower network is $\beta^* = \gamma\beta$, otherwise $\beta^* = 0$). It is worth noting that the L nodes that know the information but are unwilling to continue to spread are in a state where the information is not exposed, so the small group consisting of a U node, an A node and an L node in the information dissemination layer cannot make the "small group effect" take effect. The process of nodes interacting with their neighbors through the "small group effect" in the information dissemination layer is shown in Figure 4a, and the interaction process between nodes and their neighbors under the influence of the "small group effect" in the behavior diffusion layer is shown in Figure 4b.



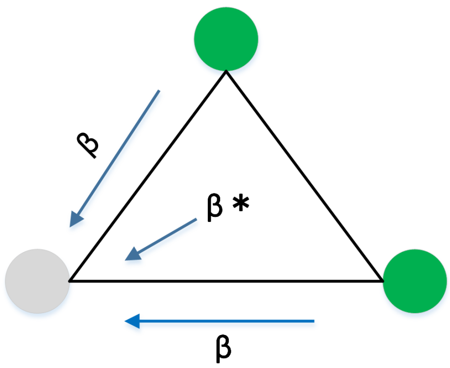


Figure 4: The interaction process of nodes with their neighbors under the influence of "small group effect": (a) information diffusion layer, (b) behavior diffusion layer.

3 Theoretical Analysis

In this section, we use the MMCA method with joint states to analyze the spreading dynamics of the proposed model. According to the model framework we proposed in Section 2, the nodes in the information-behavior coupled dynamics propagation model have the following five states: UN (unaware and not adopting behavior), AN (aware, willing to spread and not adopting behavior), LN (aware, reluctance to disseminate and not adopting behavior), AB (aware, willing to spread and adopting behavior), LB (aware, reluctance to disseminate and adopting behavior). We assume in the model that the node B that adopts the behavior will immediately feedback to the upper layer and change to the state of awareness, so we remove the state of UB (unaware and adopting behavior).

Next, we denote the probability of node i becoming UN, AN, LN, AB, LB at time t as $p_i^{UN}(t)$, $p_i^{AN}(t)$, $p_i^{LN}(t)$, $p_i^{AB}(t)$, $p_i^{LB}(t)$. In the information dissemination layer, the probability that an unaware node i which is not informed by the nearest neighbor nodes (aware individuals) is assumed to be $r_{i1}(t)$; the probability that an unaware node i which is not influenced by the "small group effect" is assumed to be $r_{i2}(t)$; the probability that an unaware node i remains unaware of the information is assumed to be $r_i(t)$.

$$\begin{cases} r_{i1}(t) = \prod_{j}[1 - a_{ji}P_j^A(t)\lambda], \\ r_{i2}(t) = \prod_{j,k}[1 - a_{ji}a_{ki}a_{jk}P_j^A(t)P_k^A(t)\lambda^*]. \end{cases} \tag{1}$$

$$r_i(t) = r_{i1}(t)r_{i2}(t). \tag{2}$$

Where $\{a_{ij}\}$ is the adjacency matrix of the information dissemination layer, $P_i^A(t) = P_i^{AN}(t) + P_i^{AB}(t)$ and $\lambda^* = \gamma\lambda$.

In the behavior diffusion layer, the probability that the node U that is unaware of the information, the node A that is aware of the information and is willing to spread it, and the node L that is aware of the information and is unwilling to spread it any more will not adopt behavior under the influence of its neighbors is assumed to be $q_{i1}^U(t)$, $q_{i1}^A(t)$, $q_{i1}^L(t)$; the probability that the node does not adopt behavior under the influence of the "small group effect" is assumed to be $q_{i2}(t)$; the probability that the nodes in the three states of U, A, and L do not adopt behavior at time t is assumed to be $q_i^U(t)$, $q_i^A(t)$, $q_i^L(t)$, respectively.

$$\begin{cases} q_{i1}^U(t) = \prod_{j}[1 - b_{ji}P_j^B(t)\beta^U], \\ q_{i1}^A(t) = \prod_{j}[1 - b_{ji}P_j^B(t)\beta^A], \\ q_{i1}^L(t) = \prod_{j}[1 - b_{ji}P_j^B(t)\beta^L]. \end{cases} \tag{3}$$

$$q_{i2}(t) = \prod_{j,k}[1 - b_{ji}b_{ki}b_{jk}P_j^B(t)P_k^B(t)\beta^*]. \tag{4}$$

$$\begin{cases} q_i^U(t) = q_{i1}^U(t)q_{i2}(t), \\ q_i^A(t) = q_{i1}^A(t)q_{i2}(t), \\ q_i^L(t) = q_{i1}^L(t)q_{i2}(t). \end{cases} \tag{5}$$

Where $\{b_{ij}\}$ is the adjacency matrix of the behavior diffusion layer, $P_i^B(t) = P_i^{AB}(t) + P_i^{LB}(t)$ and $\beta^* = \gamma\beta$.

Based on the above definition, we can obtain the state transition tree of the proposed model (see Figure 5). According to the state transition tree, we can use the MMCA method to obtain the dynamic evolution equation of the five possible states of the node:

$$\begin{aligned} P_i^{UN}(t+1) &= P_i^{UN}(t)r_i(t)q_i^U(t), \\ P_i^{AN}(t+1) &= P_i^{UN}(t)(1 - r_i(t))q_i^A(t) + P_i^{AN}(t)(1-\delta)q_i^A(t) + P_i^{AB}(t)(1-\delta)\mu, \\ P_i^{LN}(t+1) &= P_i^{AN}(t)\delta q_i^L(t) + P_i^{LN}(t)q_i^L(t) + P_i^{AB}(t)\delta\mu + P_i^{LB}(t)\mu, \\ P_i^{AB}(t+1) &= P_i^{UN}(t)r_i(t)(1 - q_i^U(t))\omega + P_i^{UN}(t)(1 - r_i(t))(1 - q_i^A(t)) \\ &\quad + P_i^{AN}(t)(1-\delta)(1 - q_i^A(t)) + P_i^{AB}(t)(1-\delta)(1-\mu), \\ P_i^{LB}(t+1) &= P_i^{UN}(t)r_i(t)(1 - q_i^U(t))(1-\omega) + P_i^{AN}(t)\delta(1 - q_i^L(t)) \\ &\quad + P_i^{LN}(t)(1 - q_i^L(t)) + P_i^{AB}(t)\delta(1-\mu) + P_i^{LB}(t)(1-\mu). \end{aligned} \tag{6}$$

Where $P_i^{UN}(t) + P_i^{AN}(t) + P_i^{LN}(t) + P_i^{AB}(t) + P_i^{LB}(t) \equiv 1$.

4 Numerical Simulation

In Section 3, we use the MMCA method to theoretically analyze the dynamic evolution process of the UAL-NBN model based on small group effect. Next, we will use the MC method [56, 57] to conduct a large number of numerical simulations to verify the accuracy of our theoretical analysis.

Here we set up a multiple network with 500 nodes in each layer, and create a scale-free network with a power exponent of 3 for the information dissemination layer, and a small-world network for the

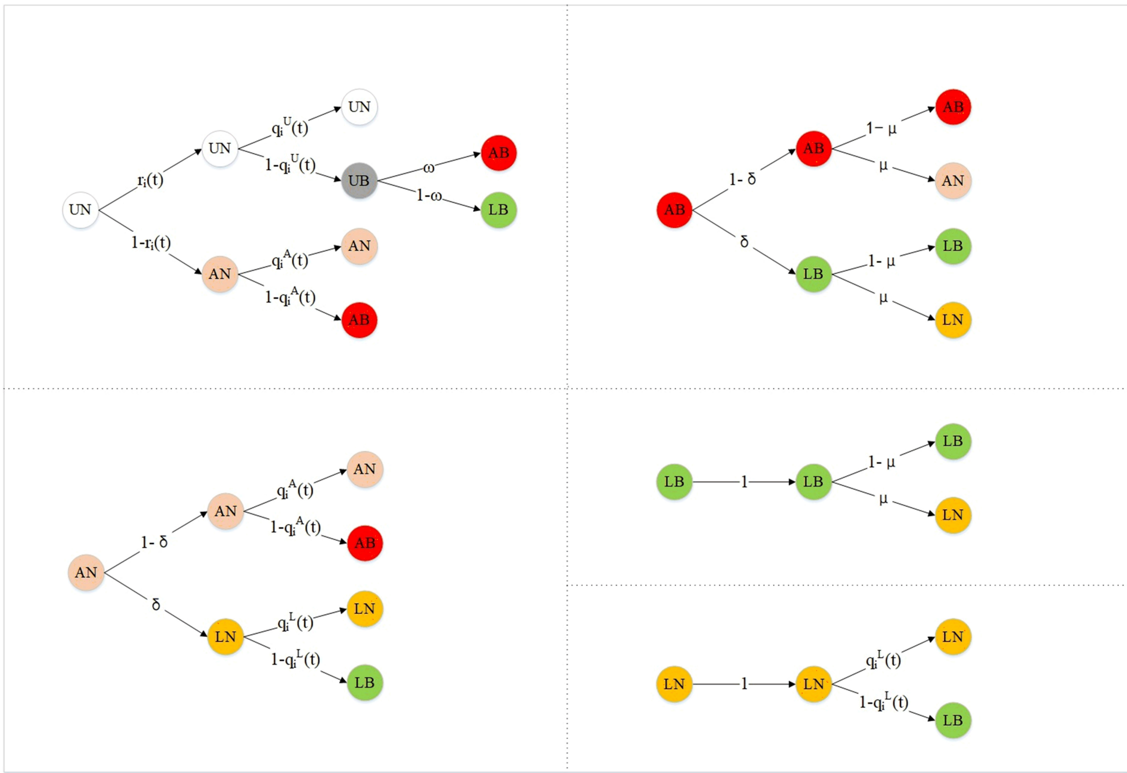


Figure 5: The state transition tree for the five possible states of the nodes.

behavioral diffusion layer connected to the nearest 4 neighbors with a reconnection probability of 0.3. In the MC simulation, we take the average of 50 loops as the final result, where each loop runs 100 time steps, and each time step runs another N micro-steps, where N is the total number of nodes in the network. When the system reaches a steady state, we use ρ^A to denote the density of individuals in the system that are conscious and willing to spread in the information dissemination layer, ρ^L to denote the density of individuals in the system that are conscious but unwilling to spread in the information dissemination layer, ρ^B to denote the total density of individuals adopting behavior in the behavior diffusion layer. Before a behavior is accepted and becomes popular, the information about it must first be widely known. In addition, we set that the L state must have been transformed by the node in the A state losing interest in the information. Thus, at the initial moment of our experiment, there will be only three states UN, AN and AB. And initially, we set, $\rho^{UN} = 1\%$, $\rho^{AN} = 1\%$, $\rho^{AB} = 1\%$.

Figure 6 shows the comparison of the evolution trends of node states in the behavioral diffusion layer with time steps obtained by the MMCA and MC methods. In Figure 6, the solid line represents the MMCA analysis result, and the dashed line represents the MC simulation result. We can clearly observe that the values obtained by both methods maintain the same trend of change, that is, for our proposed UAL-NBN model, the results of MMCA are in good agreement with those of MC simulations. This further verifies the correctness of our theoretical analysis. Based on the comparison results of the two methods, we will use the MC method to complete the subsequent experiments.

At first, we compare the proposed UAL-NBN model considering the "small group effect", the UAL-NBN model that does not consider this effect and the single-layer behavioral diffusion model NBN that does not consider the role of information and "small group effect". Figure 7 shows the evolution of behavioral diffusion in the population under these three model mechanisms. From Figure 7, we can see that compared with the single-layer behavior diffusion model, the existence of the information dissemination layer can promote the diffusion of behavior in the population, which can not only improve the adoption rate of a certain behavior, but also make the behavior spread quickly in the population. Similarly, compared with the UAL-NBN model that did not consider the "small group effect", the existence of the "small group effect" further increases the adoption rate of the behavior in the population and once again accelerates the process of behavior diffusion. We can say that the inclusion of the "small group effect" is more effective in promoting the spread of the behavior in the population than

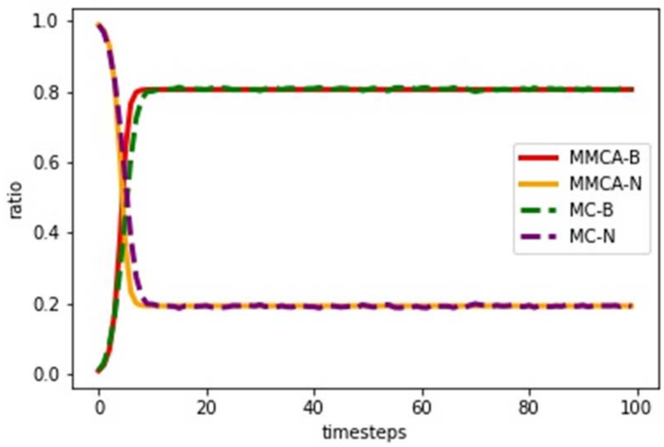


Figure 6: Comparison between MMCA analysis results and MC simulations. The parameters are set as follows: $\lambda = 0.3$, $\delta = 0.15$, $\beta = 0.3$, $\mu = 0.2$, $\sigma = 0.2$, $\omega = 0.5$, $\gamma = 0.5$.

considering only the effect of information dissemination. The reason for this phenomenon is that the "small group effect" we are considering is essentially the re-dissemination of information and behavior based on group interaction, which facilitates the evolution of the propagation process. Therefore, in real life, considering the promotion of information dissemination and the potential influence of small groups in which individuals trust and are often active can quickly increase the popularity of a certain behavior in the population.

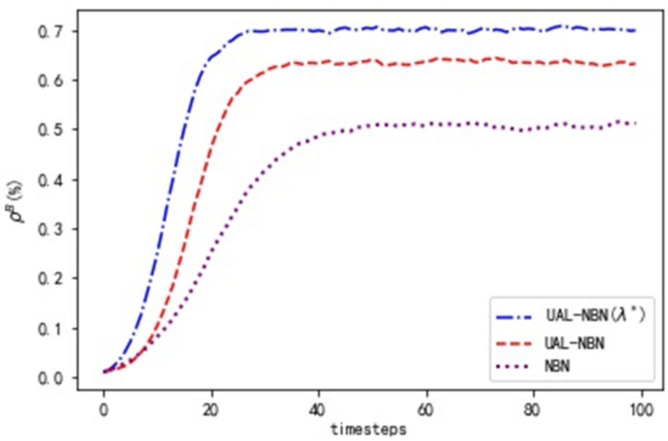
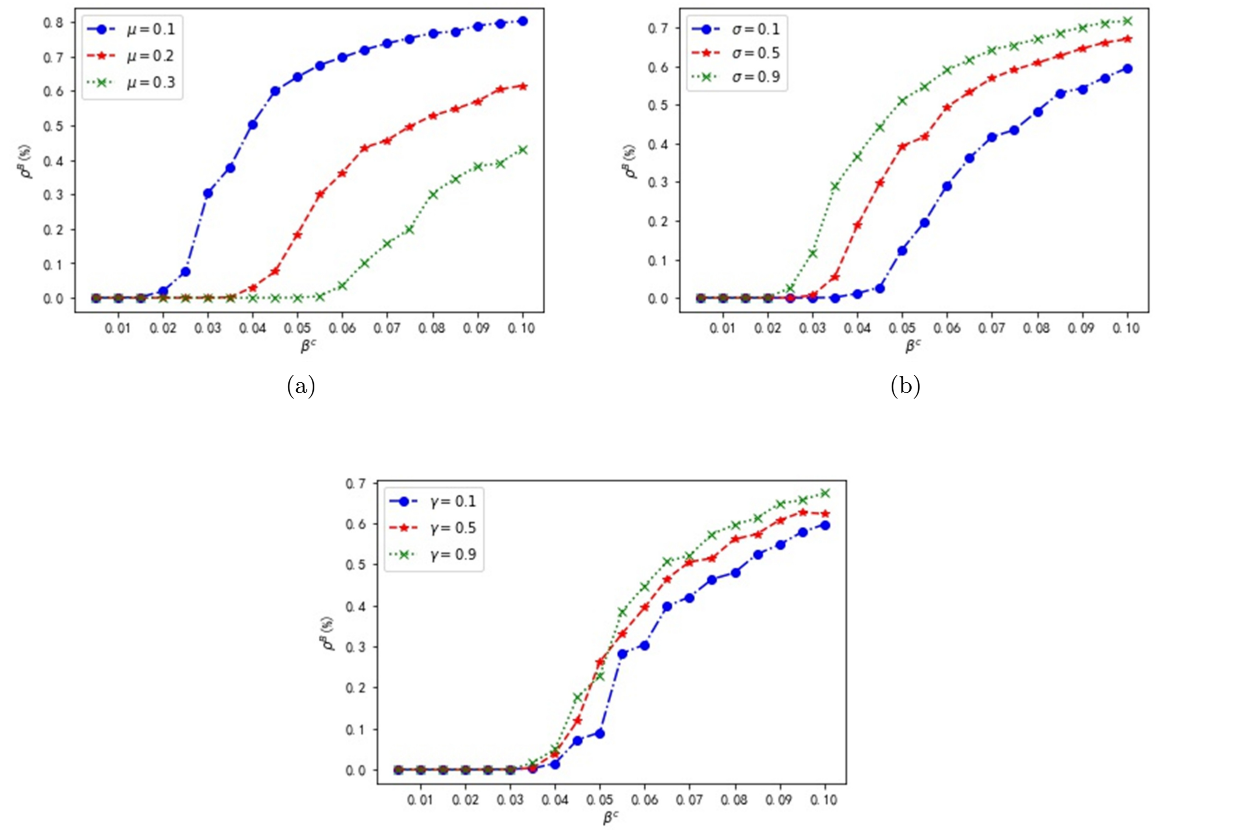


Figure 7: Comparison of the diffusion evolution trends of behavior in the population under the three model mechanisms. The blue line is the evolution trend of our proposed UAL-NBN model considering "small group effect" ($\lambda_1 = 0.3$, $\delta_1 = 0.15$, $\beta_1 = 0.1$, $\mu_1 = 0.2$, $\sigma = 0.4$, $\omega_1 = 0.5$, $\gamma = 0.9$); the red line is the multiple network model UAL-NBN that considers information dissemination but does not consider the "small group effect" ($\lambda_2 = 0.3$, $\delta_2 = 0.15$, $\beta_2 = 0.1$, $\mu_2 = 0.2$, $\sigma = 0.4$, $\omega_2 = 0.5$); the purple line is the single-layer behavioral diffusion model NBN without considering information diffusion and "small group effect" ($\beta_3 = 0.1$, $\mu_3 = 0.2$).

Above we verified the importance of the information-behavior coupling network framework considering the "small group effect" in studying behavior diffusion in the population. Next, we will continue to explore how each parameter affects the dynamics of behavioral diffusion. Figure 8 first studies the effect of various parameters on the behavioral prevalence threshold (β^c).

It can be seen from Figure 8 that on the whole, the behavior forgetting rate μ, the behavior enhancement factor ρ and the group effect factor γ have a significant impact on the behavior prevalence



(a) (b) (c)

Figure 8: In the UAL-NBN model based on the small group effect, the influence of each parameter on the behavioral prevalence threshold β^c. (a) behavioral forgetting rate μ; (b) behavior enhancement factor σ; (c) group effect factor γ. Other parameters are set to $\lambda = 0.3$, $\delta = 0.15$, $\omega = 0.5$.

threshold β^c. Specifically, in Figure 8a, as the behavior forgetting rate μ gradually decreases, the behavior prevalence threshold β^c in the system is getting smaller and smaller, and the adoption rate of the behavior in the population in steady state is also getting higher and higher. On the contrary, the greater the behavioral forgetting rate, the more difficult it is for the individual to maintain the state of adopting the behavior, which will make it more difficult for the behavior to become popular in the population. In Figure 8b, the larger the behavior enhancement factor σ, that is, the greater the promotion of information dissemination to the behavior diffusion, the smaller the threshold for the behavior to become popular in the system, and the larger the adoption rate of the behavior that the system finally achieves. In Figure 8c, we can see that the larger the group effect factor γ, that is, the greater the influence of the "small group" on the individual's behavioral decision-making, which will make the behavioral prevalence threshold smaller and smaller, and increase the adoption rate of behaviors in the crowd.

Through the above experimental results, we understand the influence of each parameter on the behavioral prevalence threshold. In order to gain a deeper understanding of the interaction between information dissemination and behavioral diffusion under the influence of the "small group effect", our next step will continue to analyze the effect of each parameter combination on the behavioral outbreak size (ρ^B).

In Figure 9, we describe the fraction of the final behavioral outbreak size (ρ^B) as a function of the combined value of behavioral diffusivity β and behavioral forgetting rate μ. It can be clearly seen from the figure that for smaller behavioral diffusivity β and higher behavioral forgetting rate μ, the scale of behavioral bursts in the population is smaller when the system reaches a steady state; and as the behavioral diffusivity β increases and the behavior forgetting rate μ decreases, the outbreak size of behavior in the population becomes larger and larger. Figure 10 shows the fraction of the final behavioral outbreak size (ρ^B) as a function of the combined value of the behavioral enhancement factor σ and the group effect factor γ. In Figure 10, we can observe that with the increase of the behavior enhancement factor σ and the group effect factor γ, that is, the greater the promotion of information dissemination on behavior diffusion, the greater the potential impact of the "small group effect" on group members, the larger the scale of the outbreak of behavior in the population. In addition, by comparing Figure 10a and Figure 10b, we can further find that the behavioral forgetting rate has a significant impact on the behavioral outbreak size in the whole system. The larger the behavioral forgetting rate, the smaller the outbreak size in the behavioral diffusion layer, and the slower the behavioral prevalence rate in the population.

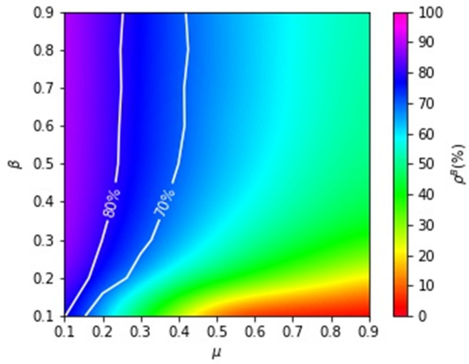
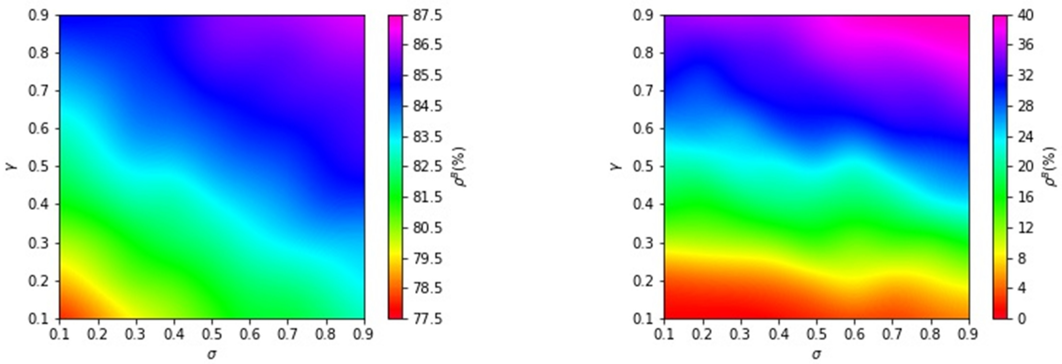


Figure 9: The fraction of the final behavioral outbreak size ρ^B as a function of the combined value of behavioral diffusivity β and behavioral forgetting rate μ.



(a) (b)

Figure 10: The fraction of the final behavioral outbreak size ρ^B as a function of the combined value of the behavioral enhancement factor σ and the group effect factor γ: (a) $\mu = 0.1$; (b) $\mu = 0.5$.

Finally, it is worth noting that the diffusion process of behavior is closely related to the network topology. Therefore, we also analyzed the random edge probability p_2 of constructing a "small group" structure in the behavior diffusion layer, that is, the effect of the density of "small group" in the behavior diffusion layer on the behavior outbreak size (ρ^B) as shown in Figure 11. By observing the Figure 11, we can conclude that with the increase of the random edge probability p_2 in the behavior diffusion layer, the speed of behavior prevalent becomes faster and faster, and the behavior outbreak size becomes larger and larger. This shows that fully mobilizing and exerting the potential influence of the "small group" structure in the population on individuals can better and faster promote the diffusion and popularization of a certain behavior at the social level.

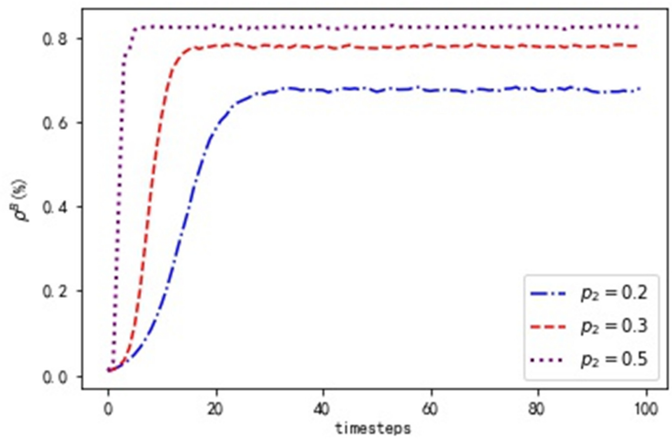


Figure 11: The influence of random edge probability p_2 on behavior outbreak size ρ^B in behavior diffusion layer.

5 Discussion and Conclusion

We establish an information-behavior coupled dynamics propagation model affected by the "small group effect", which has certain universality and can be applied to the actual dynamic process in which information dissemination affects behavior diffusion or behavior affects information, such as epidemic control, rumor governance, social behavior advocacy, and consumer marketing, etc. Next, we will illustrate the specific application of the internal mechanism of our proposed model framework with several examples.

First, we take epidemic control as an example. Our two-layer network model can be used to study how the dissemination process of disease information affects individuals to take disease prevention behaviors, thereby affecting the outbreak and control process of epidemics. In particular, all kinds of information about diseases published on online social platforms can help people to better recognize the risk of being infected by the disease, thus prompting people to take the initiative to take disease prevention behaviors. For example, the new crown pneumonia outbreak in early 2020 severely impacted social and economic development[58]. During the epidemic, the dissemination of online disease information has led to the rapid spread of disease prevention behaviors such as wearing masks, frequent disinfection, and vaccination among the population. In addition, the "small group effect" we consider can help us better understand the impact of close contact groups on the spread of epidemics, and how effective social distancing (such as severing connections in the "small group" structure) can be in the containment of epidemics.

Similarly, our model can be applied to the study of the spread of rumors, the widespread spread of which can lead individuals to make incorrect behavioral decisions and can even affect social stability. For example, the socially widespread community-wide hoarding of medicines during the epidemic and the previous salt hoarding incident, whose related information was widely disseminated on social media platforms, led to a market scramble, with demand outstripping supply and rising prices, affecting social and market stability. Our model allows us to explore the interaction between the spread of rumors and the behavior of individuals, as well as to consider the 'small group effect' that can characterize the influence of social groups on the entire fermentation process of events, so as to identify the evolutionary trends in the spread of rumors, find the strongest spreaders and develop effective governance strategies to control group behavior through rumor management.

In addition, our model can also be used for advocacy of social behavior. When we advocate a social behavior at the level of the whole society, our model can help analyze and simulate the diffusion effect of the behavior in the population. For example, in advocating low-carbon behaviors, we can actively propagate low-carbon behaviors within our ability and the benefits brought by low-carbon behaviors through online networks to enhance people's awareness of low-carbon environmental protection, so as to increase the popularity of low-carbon behaviors among the population. The "small group effect" we consider can help us further understand the extent to which the behavior of neighbors who have strong connections with themselves has potential influence on the individual's behavior. Moreover, practical problems like consumer marketing can also apply our model to help analyze and simulate the impact of marketing initiatives on consumer buying behavior, as well as the effect of recommendation of "small group" neighbors with strong connection on marketing.

However, our work is not perfect and there are certain limitations. First of all, in this paper, we only consider the "small group structure" composed of three individuals. Although three-person groups are the most common and easy to maintain and exert influence in the population, it is undeniable that there is a "small group" structure containing more individuals in the actual interpersonal network. Therefore, in the future we can further explore the influence of the structure of "small group" containing more individuals on the propagation dynamics. In addition, an individual may exist in multiple "small group" structures. In the future, we can further explore how the overlapping nodes of "small groups" affect the propagation process, and further find the nodes and small groups that have the greatest impact on the propagation process, so as to more effectively promote or inhibit the spread and popularization of behavior in the population. Finally, although the model framework we propose in this paper has certain applicability to the study of information-behavior affected by groups, in fact, the interaction between information and behavior is also affected by many other factors, such as mass media, government intervention, individual heterogeneity, time-varying of network structure, hysteresis between information and behavior, and so on. Therefore, we can further consider more influencing factors on the basis of our model, so that the model is more targeted for specific applications in specific situations and closer to reality.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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