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# OPINION EVOLUTION AND GUIDANCE MODEL BASED ON SOCIAL NETWORKS AND INFORMATION NETWORKS

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**Abstract**

In human society, opinion evolution and guidance for opinion evolution are useful for maintaining social stability, business development, and so on. To tackle these issues, we propose an opinion evolution and guidance model based on social networks and information networks (namded EGSDCN) for the first time. Firstly, we develop an opinion evolution model based on the information networks and social networks (ISOE). Specifically, we first update the individual's opinion by judging the quality of the information obtained by individual from the information network. Then, we filter the trusted neighbor set for individuals by quantifying individuals' attributes and update individual's opinion after weighting analysis of the trusted neighbor set. Finally, we conduct information exchange between the social and information networks. For guiding opinion evolution, we develop a group opinion guidance strategy based on individual stubbornness differences (termed PDGM). Specifically, we first divide the guided individuals into stubborn and non-stubborn groups. Then, for the non-stubborn group, a linear function model is used to intervene individual stubbornness. For the stubborn group, we propose the interest and opinion change functions to dynamically adjust individuals' opinion. Extensive simulation experiments have been conducted and proved that our proposed model is effective.

**Keywords:** opinion evolution, opinion guidance, dynamic stubbornness, individual authority, double-layer network

## 1 Introduction

Opinion as an expression of emotion and attitude widely exists in people's daily lives, playing a key role. Individual opinion is continually evolving due to the influence of the people and information surrounding them [1, 2, 3]. Opinion Evolution (OE) can dynamically model the evolutionary trends of group opinions to better understand changes in public social tendencies. When the evolutionary trends have a restriction on social stability, business development, etc, Opinion Guidance (OG) is a critical tool to ensure that social activities develop healthily [4, 5]. Individuals who interact with each other in social networks often exchange ideas and influence each other's opinions [6].

Current research on opinion evolution is mainly modeled in social networks [7], which can be categorized based on the type of network carriers into two forms: opinion evolution based on single-layer social networks and based on multi-layer social networks. Among them, the models based on single-layer social networks include opinion dynamics models considering the strength of interpersonal relationships and the degree of trust [8, 9, 10, 11, 12], opinion dynamics models considering opinion leaders and authoritative individuals [13, 14, 15, 16], opinion dynamics models considering the dynamic change of network topology [7, 17, 6], models of opinion evolution on multi-layer social networks include models of opinion dynamics with subject homogeneity [18, 19] and heterogeneity [20, 21] on multi-layer social networks, etc.

However, with the popularity of many online platforms and smart terminals, mobile applications such as microblogging, YouTube, and Twitter and chatbots (like ChatGPT) are emerging, which has significantly transformed the ways in which people access information. Individuals are no longer content with passively accepting the opinions from social networks; instead, they actively seek out information from information networks of the issues. Therefore, the above models fail to consider the influence of information networks on opinion evolution.

Opinion guidance is to guide some individuals in the group in a reasonable way to achieve the target opinion as much as possible. Early opinion guidance research mostly focused on the effects of changes in social network topology or changes in special nodes in the networks [22, 23, 24]. In recent years, the guidance method has been optimized. Informed agents [25, 2, 26], opinion leaders [27, 28, 29, 30, 31, 32], and medium [33, 34, 35, 5, 36] were used to guide the opinion of extreme individuals. Recently, a moderated opinion-based guidance strategy [4] has been proposed, in which the model adopts a moderate steering strategy for individuals who differ significantly from the target opinion.

However, the above guidance strategies tend to treat all individuals as if they were homogeneous, neglecting that the difficulty of changing people's opinions often varies depending on their level of stubbornness. Consequently, the above research results lay a better foundation for studying the process of users' opinion evolution and guidance and achieve a series of research results. However, the existing studies still have the following limitations:

- In opinion evolution, current research is mainly modeled in social networks. However, information in information networks exerts a significant impact on individuals' opinions. Besides, individuals interact with their neighbors and information in different ways. Existing models failed to consider the impact of information networks. In addition, existing models failed to consider the relativity when filtering authoritative individuals in social networks.
- In opinion guidance, existing strategies assume that all individuals are homogeneous and do not take into account the effects of individual differences in stubbornness on the effectiveness of guidance. In addition, the existing work uses the same guidance strategy for all individuals and does not divide the community into individuals with different levels of stubbornness and then develops different and effective guidance strategies for them.

To tackle the above issues, we propose an opinion evolution and guidance model based on social networks and information networks (termed as EGSDCN). For the opinion evolution problem, we develop an opinion evolution model based on coordination between information networks and social networks (ISOE). For the opinion guidance problem, we develop a group opinion guidance strategy based on individual stubbornness differences (PDGM). The main contributions of our research can be presented as follows:

- In order to consider the influence of information networks on the opinion evolution and opinion guidance problem, we first propose an opinion evolution and guidance model based on social networks and information networks (termed as EGSDCN). The EGSDCN model is the first to consider different rules of interaction between individuals and between individuals and information, and the first to perceive personality differences in individuals to institute different guidance mechanisms.

- We first propose a novel opinion evolution model based on coordination between social networks and information networks (termed as ISOE). In addition, because of the different ways in which individuals interact with each other and with information, we introduce two opinion evolution mechanisms in ISOE. We propose a rule for filtering relatively authoritative individuals in social networks. We realize information sharing between information networks and social networks with an inter-layer information transfer mechanism.

- Based on the ISOE model and considering the varying levels of individual stubbornness, we first propose a group opinion guidance strategy based on individual stubbornness differences (termed as PDGM). For the non-stubborn group, we utilize a linear function model to dynamically model the evolution of their stubbornness. For the stubborn group, we apply two trigonometric function models to dynamically reflect the changes in their interests and opinions.

## 2 Related work

Opinion evolution research focuses on dynamically modeling the trends and changes in group opinions. Opinion guidance models serve as powerful tools for guiding these opinions toward socially desirable. In this section, we will provide an overview of the current research landscape concerning opinion evolution and opinion guidance models.

### 2.1 Opinion Evolution Model

The Opinion Evolution Model is an important tool to study the process of opinion formation, dissemination, and evolution of individuals in society.

Trust is a typical relationship in social networks. Changes in the level of trust significantly impact human interaction and opinion exchange. Kozitsin et al. [8] verified that the existence and magnitude of positive and negative opinions are positively related to the distance in opinions between a user and their friends. Li et al. [10] constructed a dynamic multiple attribute group decision framework according to a social trust network, which considered the impact of trust propagation of experts on decision-making results.

Opinion leaders have significant influence and appeal in group activities, shaping the opinions of others and even possessing the power to reverse public sentiment through their discourse abilities. Chen et al. [14] analyzed the impact of leaders with competitive opinions on group opinions from four characteristics: reputation, stubbornness, appeal, and extremeness. Chen et al. [15] proposed a public opinion control strategy according to public authority under the HK model, which studied how to utilize the influence of experts or authorities to reach the best consensus on public opinion in the shortest time.

A single network structure serves as a basic theoretical framework in network science. However, this stands in contrast to the real world, which comprises numerous interconnected and interdependent complex networks. Currently, various types of multi-layer networks are becoming the latest frontier topics in network science. WX et al. [20] studied the percolation-cascading process on a multi-layer network with different coupling opinions. Wang et al. [21] proposed a two-layer time-varying trust HK model consisting of a leader layer and a follower layer and investigated the effects of changing inter-individual opinion differences on inter-individual trust relationships.

### 2.2 Group Opinion Guidance Strategy

Opinion guidance is to guide some individuals in the group in a reasonable way to achieve the target opinion as much as possible.

Early, many opinion guidance strategies to render some nodes ineffective were proposed, including the node immunity strategy and node enforced silence strategy. In addition, opinion guidance was also achieved by controlling the position of key nodes in a social network. Qian et al. [22] proposed an adaptive bridge control strategy, which achieves the guidance effect by controlling a special type of nodes (bridge nodes). Gong et al. [24] proposed a structural hole-based group opinion control method using the Friedkin-Johnsen model.

Informed agents are instrumental in guiding groups toward consensus on socially desirable opinion. Fan et al. [2] proposed an opinion dynamics model based on social judgment, distinguished between internal and external opinions, and incorporated the idea of compromise between similar opinions and exclusion between dissimilar opinions. Afshar et al. [26] studied how informed agents move public opinion towards socially desirable goals through microinteractions.

Opinion leaders in social networks have a significant advantage in guiding users' opinions toward consensus during the decision-making process. Chen et al. [29] improved the HK model by incorporating opinion similarity and proximity, and they investigated the dynamic process through which opinion leaders influence their followers. Ebadizadeh et al. [31] introduced a rumor propagation model with controller individuals.

The above guidance strategies directly altering individuals' opinions or forcing target opinions on them can undermine the research's validity and practicality. A moderated opinion-based guidance strategy [4] first calculates the distance between the interacting parties' opinions. If the individual is likely to accept the target opinion, it is directly pushed. Conversely, if the target opinion is too distant, a more moderate opinion is presented to the individual.

# 3 Research motivation

Since the outbreak of COVID-19 in 2020, it has not only led to the country's overall downturn in the employment environment but also profoundly changed young people's opinions on careers and employment preferences. Under such an environment, more and more college students are more inclined to choose careers that are more stable and with a low risk of unemployment. Especially in China, positions such as civil servants and institutions are highly favored.

The above factors together contribute to the fact that when the Chinese college student population is faced with employment choices, civil servants, career organisations, and other positions of a stable nature become their preferred targets [37]. This kind of behavior has also inadvertently encouraged university students who do not have any employment goals to blindly follow the crowd's behavior, which in turn has led to the phenomenon of 'public examination fever' nowadays.

This reflects the significant bias of college students in the choice of employment. This situation not only leads to the failure of the state and social investment in higher education to be fully and effectively utilized, but also depletes young people's valuable time, energy, and creative potential.

In the process of rapid social development, similar phenomena are not uncommon. In view of such problems, there is an urgent need for effective means of guiding opinions. Reasonable guidance can promote the healthy development of social opinion and help the smooth implementation of national policies and social harmony and stability.

# 4 The proposed model (EGSDCN)

In this article, we propose an opinion evolution and guidance model based on social networks and information networks (EGSDCN), which includes two parts: The opinion evolution model based on coordination between information networks and social networks (ISOE) and the group opinion guidance strategy based on individual stubbornness differences (PDGM).

**Problem Formulation**. The question examined in this work is how individuals' opinions change and are guided over time in collaborative networks.

## 4.1 Opinion Evolution Model based on Coordination between Information Networks and Social Networks (ISOE)

In this section, we introduce the construction process of the ISOE model. Firstly, some relevant descriptions of the ISOE model are defined as follows:

**Definition 1: Users Set**. Let $U = \{u_1, u_2, \ldots, u_n\}$ represents the set of users, where $n$ is the size of the users set. Each user in $U$ is identified with a user ID.

**Definition 2: Information Set**. Let $F = \{f_1, f_2, \ldots, f_n\}$ represents the set of information, where $n$ is the size of the information set. Each information in $F$ is identified with a information ID.

**Definition 3: Opinion Set**. Each user in the social network changes their opinions over time. Let $X(t) = \{x_1, x_2, \ldots, x_n\}$ denotes opinion set. $x_i^{(t)} \in [0,1]$, and n in social network denotes the number of users in social network, n in information network denotes the number of information in information network.

**Definition 4: Multi-Layer Network Structure**. Let $M = (g, L)$ denotes multi-layer network structure, and $g = \{G_\alpha; \alpha \in \{1, \ldots, M\}\}$ denotes the set of graphs. $G_\alpha = (V_\alpha, E_\alpha)$, and $V = \{v_1, v_2, \ldots, v_n\}$, $V$ denotes set of nodes, $E = \{e_{ij}\}$, $E$ denotes set of sides. $L = \{E_{\alpha\beta} \subseteq (V_\alpha \times V_\beta); \alpha, \beta \in \{1, \ldots, M\}, \alpha \neq \beta\}$ denotes the set of sides between layers [38], where $M$ denotes the number of networks. In this work, $M = 2$, and $g$ denotes a social network and an information network; $L$ denotes the relationship of social networks and information networks.

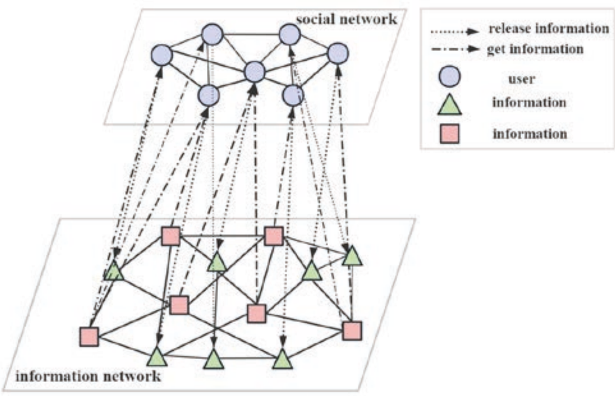


**Figure 1**. The structure of the ISOE model.

The structure of the ISOE model is shown in Figure 1. It is mainly divided into two layers: the upper layer is the social network layer (LS), and the lower layer is the information network layer (LI). The layer LS denotes the offline and online social relationships of individuals, and the layer LI denotes information from information networks. Nodes in the layer LS represent users, nodes in the layer LI represent information, and each user and information expresses an opinion. The square and triangle nodes in the information network represent the information that an individual obtains from the network and the information that an individual publishes, respectively.

In social networks, individuals are more familiar with the personality characteristics of their neighbors, and thus, when interacting with their neighbors' opinions, they consider factors such as the closeness of relationships, the authority of the individuals, and the degree of trust. In contrast, in information networks, whether the information is actively collected by individuals or pushed by big data, the primary factor determining a piece of information's influence on individual opinion is its quality—encompassing content, source, and other relevant attributes [39]. In this work, we introduce two different opinion evolution strategies: opinion evolution processes in information networks and opinion evolution processes in social networks. In addition, we introduce a coordination mechanism between information networks and social networks. The specific evolution process of the ISOE model is as follows:

(1) The evolution of individuals in information networks:

The content($\delta$), source($\varepsilon$), and external identity (the number of likes ($N_{like}$), comments ($N_{comment}$), and sharing ($N_{share}$)) of information are the most favorable indicators for judging the truth and reliability of the information. The calculation is defined as Eq. (1):

$$E = \alpha N_{like} + \beta N_{comment} + \gamma N_{share} \tag{1}$$

where $E$ denotes the sum of external factors; $\alpha$, $\beta$, $\gamma \in [0, 1]$, $\alpha + \beta + \gamma = 1$, $\alpha$, $\beta$, and $\gamma$ denote respectively the weight of $N_{like}$, $N_{comment}$, and $N_{share}$.

The normalization formula of $E$ is defined in Eq. (2):

$$\Gamma = \frac{E - E_{min}}{E_{max} - E_{min}} \tag{2}$$

where $\Gamma$ indicates the normalized $E$, $E$ indicates original value, $E_{min}$ indicates minimal value of $E$ of all information, $E_{max}$ indicates maximal value $E$ of all information.

In this work, the above three variables are used to assign weights to the information acquired by individuals in the information network. The formula is defined in Eq. (3):

$$W_{ij}(t) = a\delta_j + b\varepsilon_j + c\Gamma_j \tag{3}$$

where $a, b, c \in [0, 1]$, $a + b + c = 1$, $a$, $b$, and $c$ denote respectively the proportion of $\delta_j$, $\varepsilon_j$, and $\Gamma_j$ in calculating information weight.

We calculate the opinion of an individual $x_i$ in information networks at time $t + 1$ according to the opinion evolution formula (4).

$$x_i^{(t+1)}(info\_net) =$$

$$\begin{cases} \Phi_i x_i^{(0)} + (1-\Phi_i)\sum_{j=1}^{n} W_{ij}x_j(t), t=1 \\ \Phi_i x_i^{(t+1)}(social\_net) + (1-\Phi_i)\sum_{j=1}^{n} W_{ij}x_j(t), t>1 \end{cases} \quad (4)$$

where $\Phi_i$ denotes the stubborn parameter of individuals, $x_i^{(0)}$ denotes the initial opinion of an individual $x_i$, $x_i^{(t)}(social\_net)$ denotes the opinion from the social network, $x_j(t)$ denotes a piece of information and $W_{ij}$ denotes the information weight.

(2) The evolution of individuals in social networks:

We first introduce the concept of individual cognitive ability, which outlines the differences between individuals in terms of their education and personal experience. In this work, we filter the authoritative neighbors for the current individual according to the parameter of individual cognitive ability $(c_i)$. In other words, only the neighbors whose cognitive ability is higher than their own and exceeds the individual cognitive ability threshold $(\rho)$ are identified as the authoritative neighbors for the current individual, and the individual trusts the authoritative neighbors directly. Then, for the neighbors that do not satisfy the authority condition, this work uses the inter-individual intimacy $(R_{ij})$ to measure the degree of trust between individuals. In other words, the neighbors that exceed the inter-individual intimacy threshold $(\sigma)$ are identified as the neighbors that the current individual trusts. Finally, this work assigns different weights to the neighbors trusted by an individual and then updates its own opinion. The specific evolution process is as follows:

**(1) Trust Set (I)**: At time t, the trust set for $v_i$ is composed of $v_i$'s authoritative neighbors and neighbors who meet the intimacy threshold $\sigma$ among neighbors who are in an equal position with $v_i$. The rules for filtering trust set in neighbors are described as Eq. (5):

$$I_i(t) = \{v_j|(c_j - c_i > \rho) \cup (|c_j - c_i| < \rho, R_{ij} > \sigma)\} \quad (5)$$

**(2) Distrust Set (J)**: At time t, the distrust set for $v_i$ is composed of neighbors that are neither authoritative neighbors of $v_i$ nor meet the intimacy thresholds. The rules for filtering distrust neighbors are described as Eq. (6):

$$J_i(t) = \{v_j|(c_i - c_j > \rho) \cup (|c_j - c_i| < \rho, R_{ij} < \sigma)\} \quad (6)$$

**(3) Unconnected Set (K)**: At time t, the unconnected set for $v_i$ contains the nodes that are not visited by $v_i$, which is presented as Eq. (7):

$$K_i(t) = \{v_j|e_{ij}(t) = 0\} \quad (7)$$

In this work, we assign weights to neighbors based on individual authority and inter-individual closeness, and the weighting formula is is described as Eq. (8):

$$\Theta_j = lc_j + mR_{ij} \quad (8)$$

where $l,m \in [0,1]$, $l+m=1$, $l$ and $m$ denote respectively the proportion of individual cognitive ability and intimacy between individuals when calculating the importance of individuals in the trust set to the current individual.

The weight of individuals is described as Eq. (9):

$$w_{ij}(t) = \begin{cases} \frac{\Theta_j}{\sum_{k\in I_i^t(\Theta_k)}}, & if \quad v_j \in I_i(t) \\ 0, & otherwise \end{cases} \quad (9)$$

We calculate the opinion of an individual $x_i$ in the social network at time $t+1$ according to the opinion evolution formula (10).

$$x_i^{(t+1)}(social\_net) = (1-\Phi_i)\sum_{j\in I_i^t} w_{ij}x_j(t) + \Phi_i x_i^{(t+1)}(info\_net) \quad (10)$$

where $\Phi_i$ denotes the stubborn parameter of individual, $x_j(t)$ denotes the opinion of a neighbor of individual $x_i$, $x_i^{(t+1)}(info\_net)$ denotes the opinion from the information network, and $w_{ij}$ denotes the weight of individuals.

(3) Coordination processes in information networks and social networks

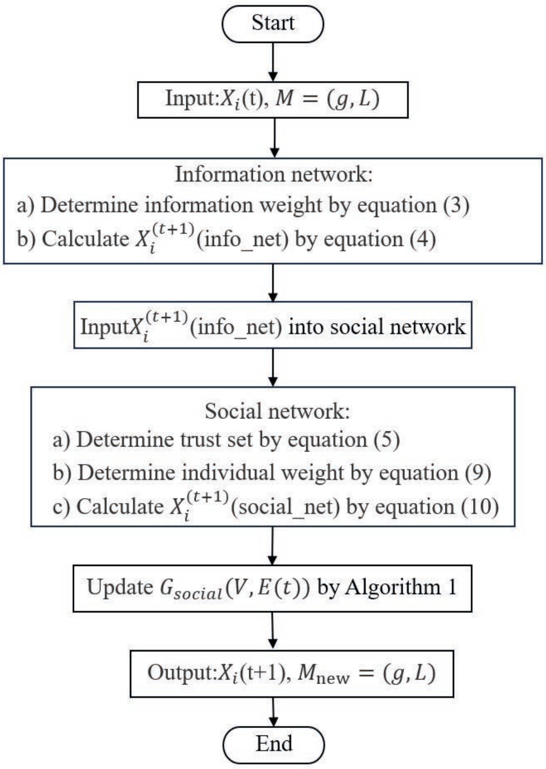


**Figure 2**. The opinion evolution process from time $t$ to $t+1$ $(t \geq 1)$

Individuals' opinions exist in the form of information in the information network; in other words, users can obtain information from information networks, and they can also publish their opinions on information networks. Therefore, this work assumes that the individual's opinion changes through the alternating evolution of the information network and the social network and finally forms its own opinion. In addition, in the collaborative network model, after each round of opinion evolution, the opinions in the social network and the information in the information network will be synchronously updated through the inter-layer information transfer mechanism. Specifically, in the information network, once the evolution process is over, the updated information of individuals will be inputted into the social network due to the existence of connecting edges between layers. The same operation is performed in social networks. The concrete steps are shown in Figure 2.

(4) Update process for social networks

Many previous opinion dynamics models assume that the social network was static. However, in reality, interpersonal relations can disappear or be reestablished for various reasons, which result in changes and evolution in social networks over time [7]. Therefore, we propose a dynamic updating method for social network topology, which is presented in Algorithm 1.

**Algorithm 1** Social Networks Topology Updating Rules

**Input:** The initial network $G(U, E(t))$, $C$, $R$, $\rho$, $\sigma$
**Output:** The updated network $G(U, E(t+1))$

**for** $v_i \in J_i(t)$ **do**
  Find $v_h$ who has the lowest intimacy to $v_i$
  $G.remove\_edges\ (v_i, v_h)$
**end for**
**for** $v_i \in K_i(t)$ **do**
  Find $v_q$ who has the largest authority
  $G.add\_edges\ (v_i, v_q)$
**end for**

## 4.2 Group Opinion Guidance Strategy based on Individual Stubbornness Differences (PDGM)

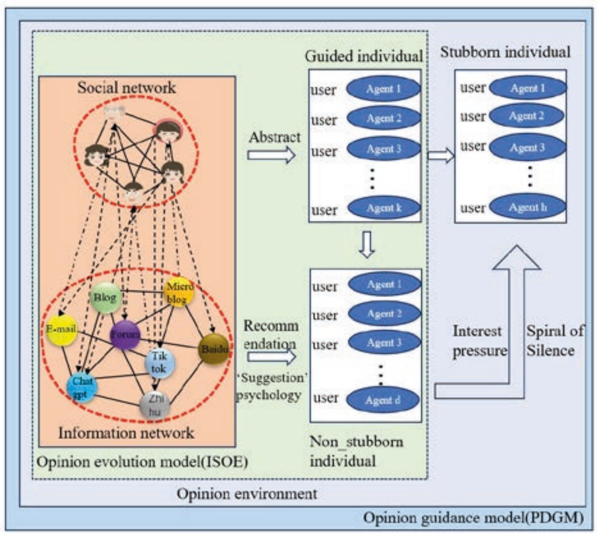


**Figure 3**. The structure of the PDGM model.

In this section, we introduce the construction process of the PDGM model, which develops two different opinion guidance strategies based on individual differences in stubbornness. Therefore, this model is mainly divided into two parts: the opinion guidance for non-stubborn individuals and opinion guidance for stubborn individuals. The structure of the PDGM model is shown in Figure 3.

Firstly, some relevant descriptions of the model construction process of the PDGM strategy are defined as follows:

**Definition 1: Individual stubbornness**. Stubbornness refers to a person's stubbornness in holding on to his or her opinions and unwillingness to change or compromise. In this work, it is assumed that individual stubbornness is heterogeneous. In this work, we let $\Phi_i$ denotes the individual stubbornness, $\Phi = \{\Phi_1, \Phi_2, \Phi_3, \ldots, \Phi_n\}$, $\Phi_i \in [0,1]$. where the larger the $\Phi_i$, the higher the individual stubbornness.

**Definition 2: The decline of interest**. In the process of opinion guidance, the majority of individuals gradually converge to the socially desirable opinion. As the proportion of positive opinions increases, the attention, credibility, and authority of the stubborn individuals with negative opinions decrease, which is referred to as the 'decline of interest' in this work, and we let $\bigtriangledown$ denotes the decline of interest.

**Definition 3: The amount of opinion change**. In the process of interest reduction, the stubborn individual has to change his or her opinion to match the existing 'superior' opinion. In this work, we let $\bigtriangleup$ denotes the amount of opinion change.

(1) Guidance Model Construction for Non-stubborn Extreme Individual

For the extreme non-stubborn individuals, intelligent information recommendation technology and 'suggestion' psychology are used to intervene in the stubbornness of individuals. In this work, a linear function model is designed to describe the dynamic change process of individual stubbornness under the influence of intelligent information recommendation and 'suggestion' psychology.

The influence of the 'suggestion' effect on individual stubbornness is mainly reflected in two aspects:

i **Reinforcement effect:** of all the opinions with which an individual interacts, when an individual receives more similar opinions than opposing ones, it leads to a reinforcement effect on their original opinion. This reinforcement increases their level of stubbornness, making it more challenging for them to accept contrary opinion.

ii **Restrain effect:** of all the opinions with which an individual interacts, when an individual receives more opposing opinions than similar ones, it leads to a restraint effect on their original opinion. This restraint effect decreases their level of stubbornness, making them more likely to accept the opposite opinion.

In this work, we design a formula for the dynamics of individual stubbornness. The formula is defined in Eq. (11):

$$\Phi_i^{(new)} = \begin{cases} k\Phi_i + k_1, & N_{similar} > \frac{1}{2} \\ \Phi_i, & N_{similar} = N_{opposite} \\ k\Phi_i - k_2, & N_{opposite} > \frac{1}{2} \end{cases} \tag{11}$$

where $\Phi_i^{(new)}$ denotes the new stubbornness, and $\Phi_i$ denotes original stubbornness.

The evolution formula for the opinions of non_stubborn extreme individuals is defined in Eq. (12):

$$\begin{aligned} &x_i^{(t+1)}(non\_stubborn) = \\ &\Phi_i^{(new)} x_i^{(t)} + \\ &(1-\Phi_i^{(new)})[\sum_{j\in I_i^t} w_{ij}x_j(t) + x_i^{(t+1)}(info\_net)] \end{aligned} \tag{12}$$

where $\Phi_i^{(new)}$ denotes the new stubbornness, $x_i^t$ denotes individual opinion in the last round, $\Phi_i$ denotes the stubborn parameter of individual, $x_j(t)$ denotes the opinion of a neighbor of individual $x_i$, $x_i^{(t+1)}(info\_net)$ denotes the opinion from the information network, and $w_{ij}$ denotes the weight of individuals.

(2) Guidance Model Construction for Stubborn Extreme Individual

In this work, we consider the trust between individuals, the attention they receive, and the authority they possess as benefits. We design a loss-of-interest function that describes how an individual's interests change in response to the proportion of positive opinions in the 'opinion environment'. Based on this function, we further construct an opinion change function, which quantifies the degree of change in an individual's opinion when faced with a loss of interest. This model offers a new perspective for understanding the behavior of stubborn individuals in group dynamics.

The decline of interest is closely related to the proportion of positive opinions in the group. Thus, we first calculates the proportion of the number of people holding positive opinions, and its calculation formula is defined in Eq. (13):

$$x = \frac{num_{positive}}{num_{all}} \tag{13}$$

where $num_{positive}$ denotes the number of people in the group with a positive opinion, and $num_{all}$ denotes the total number of people in the group.

Individuals' interests ($\bigtriangledown$) vary with the number of positive opinion holders. When the number of individuals with a positive opinion is low, the interest of the individuals with negative opinion declines slowly; when the number of individuals with a positive opinion increases, the interest of individuals with negative opinions declines rapidly. Therefore, the rate of interest decline shows a trend of slow and then rapid. We use a variant of the trigonometric function to describe the change. The formula is defined in Eq. (14):

$$\bigtriangledown = sin(\pi x)\ x \in (0.5, 1) \tag{14}$$

The amount of opinion change ($\triangle$) resulting from a loss of interest can be expressed as Eq. (15):

$$\triangle = 1 - cos[\frac{\pi}{2}(1-\bigtriangledown)]\ (1-\bigtriangledown) \in (0, 0.5) \tag{15}$$

The evolution formula for the opinions of stubborn extreme individuals is defined in Eq. (16):

$$x_i^{(t+1)}(stubborn) = \\ \Phi_i x_i^t + (1-\Phi_i)[\sum_{j \in I_i^t} w_{ij} x_j(t) + x_i^{(t+1)}(info\_net) + \triangle] \tag{16}$$

where $\Phi_i$ denotes the stubborn parameter of individual, $x_j(t)$ denotes the opinion of a neighbor of individual $x_i$, $x_i^{(t+1)}(info\_net)$ denotes the opinion from the information network, and $w_{ij}$ denotes the weight of individuals.

(3) Guidance Model Construction for Ordinary Individual

This work assumes that ordinary individuals are not directly guided, but only extreme individuals are guided in the public opinion polarization phenomenon. The evolution of the opinions of ordinary individuals still follows the evolutionary rules set by the ISOE model. The evolutionary rule for the ordinary individual is defined in Eq.(17) and Eq.(18).

$$x_i^{(t+1)}(info\_net) = \\ (1-\Phi_i) \sum_{j \in I_i^t} w_{ij} x_j(t) + \Phi_i x_i^{(t+1)}(social\_net) \tag{17}$$

where $\Phi_i$ denotes the stubborn parameter of individual, $x_j(t)$ denotes the opinion of a neighbor of individual $x_i$, $x_i^{(t+1)}(social\_net)$ denotes the opinion from the social network, and $w_{ij}$ denotes the weight of individuals.

$$x_i^{(t+1)}(social\_net) = \\ (1-\Phi_i) \sum_{j \in I_i^t} w_{ij} x_j(t) + \Phi_i x_i^{(t+1)}(info\_net) \tag{18}$$

where $\Phi_i$ denotes the stubborn parameter of individual, $x_j(t)$ denotes the opinion of a neighbor of individual $x_i$, $x_i^{(t+1)}(info\_net)$ denotes the opinion from the information network, and $w_{ij}$ denotes the weight of individuals.

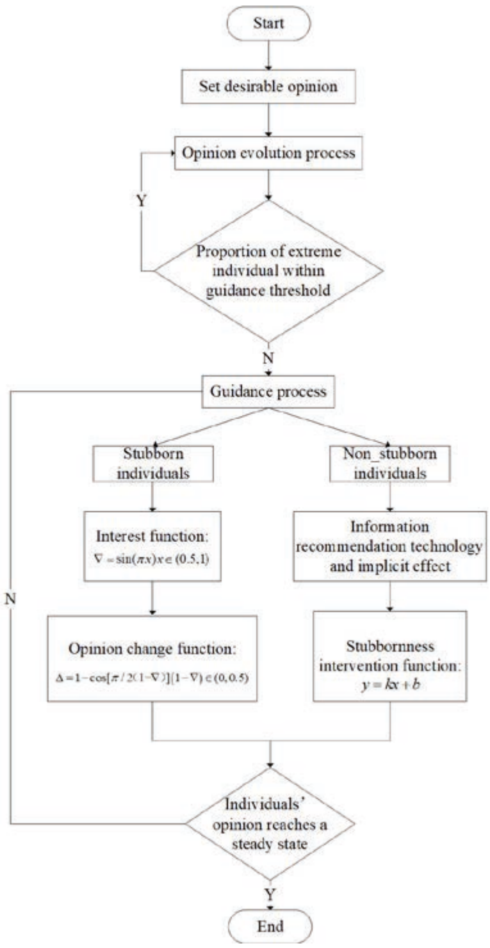


**Figure 4**. Flowchart of group opinion guidance strategy based on individual stubbornness differences

The detailed flow of the PDGM model is shown in Figure 4. The detailed steps in the construction of the PDGM model are shown in Algorithm 2.

**Algorithm 2** Evolution Process for the Proposed Model

**Input:** The initial network $M=(g,L)$, the initial opinions $X(0)$, $C_i$, $R_{ij}$, $\rho$, $\sigma$, $\Phi_i$
**Output:** The final opinions $X(t)$

1: Setting maximum iteration rounds: $t_{max\_rounds}$
2: **for** $t=0 \rightarrow t_{max\_rounds}$ **do**
3: Opinion evolution in information network:
4: **for** each user $u_i \in U$ **do**
5: Information weight is calculated by formula (3).
6: Determine the $X^{(t+1)}_{info\text{-}net}$ by evolution rule (4).
7: **end for**
8: Opinion evolution in social network:
9: Input opinions obtained from the information network $X^{(t+1)}_{info\_net}$ into the social network.
10: **for** each user $u_i \in U$ **do**
11: Determine the trust set of $u_i$ by regulation (5)
12: The neighbor's weight is calculated by formula (9):
13: Determine the $X^{(t+1)}_{social\text{-}net}$ by formula (10)
14: **end for**
15: Input opinions obtained from social networks $X^{(t+1)}_{social\_net}$ into the information network.
16: Determine whether the guidance threshold has been reached.
17: Group opinion guidance process:
18: Classify extreme individuals into stubborn and non-stubborn groups.
19: **for** non-stubborn extreme individual $v_i$ in $g_{social\_net}$ **do**
20: Calculate the change of stubbornness by formula (11).
21: Update the opinions of non-stubborn individuals by formula (12).
22: **end for**
23: **for** stubborn extreme individual $v_i$ in $g_{social\_net}$ **do**
24: Calculate opinion environment by formula (13).
25: Calculate the amount of change in benefits by formula (14).
26: Calculate the amount of change in opinion by formula (15).
27: Update the opinions of stubborn individuals by formula (16).
28: **end for**
29: **end for**
30: **if** $norm(X^{(t)}_{social\text{-}net} - X^{(t+1)}_{social\text{-}net}, np.inf) < eps$ **then**
31: Output the final opinions $X(t)$
32: **else**
33: Go to step 2
34: **end if**

# 5 Experiments

In this work, a multi-agent modeling and simulation approach was adopted to simulate the EGSDCN model in a PyCharm development environment using the Python programming language. These experiments successfully verified the validity of the EGSDCN. In order to further explore the effects of each parameter on the performance of the proposed model, the guidance effect of the model is evaluated under different initial data distributions and different distributions of the percentage of stubborn individuals, respectively.

In a Small World (WS) network, most nodes are not directly connected. However, the majority of nodes may be reached from any other node in just a few steps. This characteristic is more suitable for modeling the interpersonal relations of real society. On the other hand, in an Erdos-Renyi (ER) network, the presence of edges between nodes is random and determined by a probability P, which is more suitable for the interpersonal relations of the virtual world. Therefore, we validate the advantage and reliability of the proposed model by one ER network and one WS network.

In order to eliminate the potential interference of the change of opinions on the experimental results, all data were collected after the model had reached a steady state and were averaged over 100 experiments. The maximum step size is set to 10000.

## 5.1 Analysis of the evolution and guidance process of public opinion

To validate the advantages of the ISOE model, we treat the single network model as the baseline model, and we use opinion evolution steps (ES) to measure how fast a model reaches the stable stat.In the experiment, to avoid the randomness of parameters, the individual cognitive ability threshold $\rho$ and the threshold of intimacy between individuals $\sigma$ use default values, and 100 repeated experiments were conducted in each case to statistically analyze the results. Figure 5, and Figure 6 presents the experimental results, where the X-axis means the rounds that opinion evolution reaches a stable state, and the Y-axis means the opinion value.

From Figure 5 and Figure 6, we can see that, compared to the single social network model, in the ISOE model, group opinions reach a stable state more quickly, and the dispersion degrees of group opinions in the final state are lower and converge to a narrow vale range, which means a consensus state can be reached.

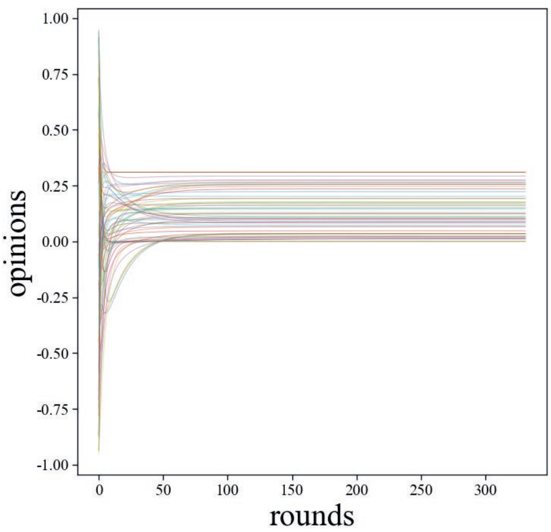


**Figure 5**. Analysis of the opinion evolution process in social network.

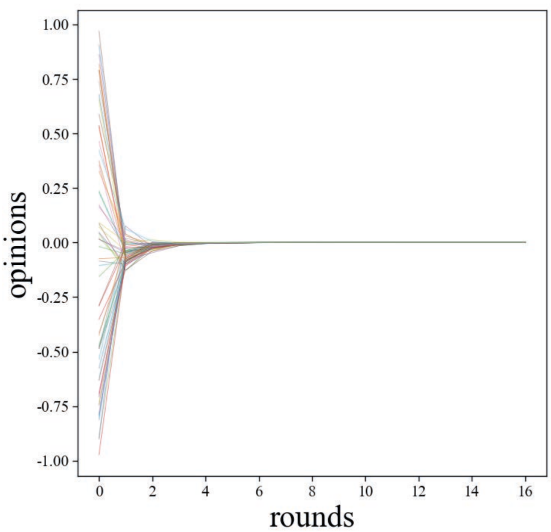


**Figure 6**. Analysis of the opinion evolution process in ISOE.

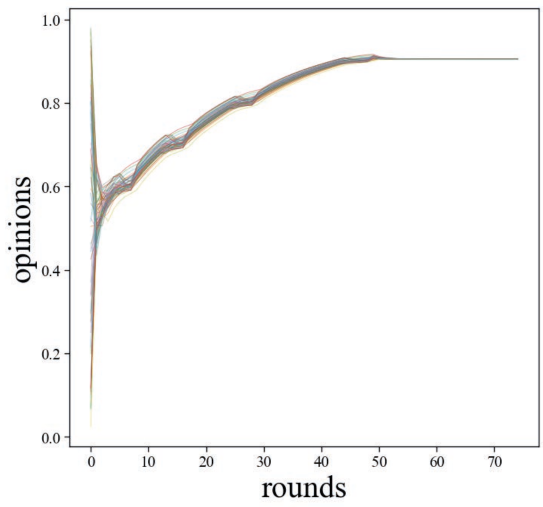


**Figure 7**. Analysis of the opinion guidance process.

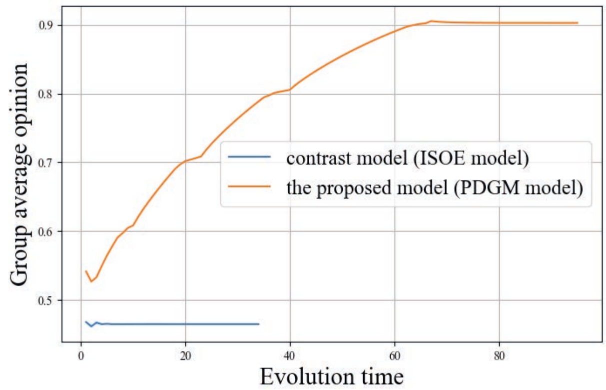


**Figure 8**. Trends in the group's average opinions of the ISOE model and the PDGM model.

In order to verify the effectiveness of the PDGM model, this work adopts the ISOE model (Figure 6) as a comparison model. In this work, we simulate the opinion evolution trend of ISOE and PDGM models, the socially desirable opinion set to 1.0, and the rest of the parameters as default values. The experiment was stopped when the group's opinions reached a steady state or reached the maximum step size, and the number of evolutionary steps was used as the speed of opinion evolution. The simulation results are shown in Figure 5, Figure 6,Figure 7 and Figure 8. The X-axis of Figure 5, Figure 6 and Figure 7 represents the step size when the group's opinions reach a steady state, and the Y-axis represents the individual opinions; the X-axis of Figure 8 represents the step size when the group's opinions reach a steady state, and the Y-axis represents the average opinions of the group.

In the PDGM model, we do not establish an opinion similarity threshold. This means that individuals do not base their trust in their neighbors' opinions on the similarity of those opinions. Instead, they determine whether to trust a particular neighbor or a piece of information based on their own personality traits, the characteristics of their neighbors, or the attributes of the information itself. To validate the effectiveness of our proposed guidance strategy, we employ the principles of the DeGroot model. The results of the experiment are shown in Figure 6. When the group's opinion reaches a steady state, only a cluster of opinions centered around a neutral attitude emerges.

From Figure 5 and Figure 6, we can observe that the PDGM model with a guidance strategy (Figure 7) is more effective in aligning the group's opinions with socially desirable opinion within a certain time, compared to the ISOE model without a guidance strategy (Figure 6). The reason for this is that, in the PDGM model, individuals are continuously exposed to information containing socially desirable opinion, which is recommended by intelligent information recommendation technology. Under the influence of this 'suggestion' effect, individuals' stubbornness towards their initial opinions gradually diminishes, while their trust in the information presenting socially desirable opinion increases. Consequently, individual opinions progressively change towards the socially desirable ones, thereby achieving the goal of opinion guidance.

Figure 8 simulates the trend of the average opinion of the group for the ISOE model and the PDGM model. Since the ISOE model and PDGM model are constructed on the basis of the DeGroot model. Therefore, the group's opinion will reach a steady state at 0.5. Therefore, in the ISOE model, the group's average opinion is 0.5, while in the PDGM model, due to the presence of the guidance strategy, the group's average opinion grows gradually between [0.5,1], and ultimately reaches the socially desirable opinion.

## 5.2 The influence of internal parameters on ISOE model

In this section, we conduct an experiment to investigate the effects of the size of individual cognitive ability threshold $\rho$ and intimacy threshold $\sigma$ on the model performance. We verify the effects of $\rho$ and $\sigma$ in both the single social network model and the ISOE model. We treat $\rho$ and $\sigma$ as variables while keeping the remaining parameters constant. The experimental results are presented in Figure 9 and Figure 10. In Figure 9, the X-axis represents the individual cognitive ability parameter and intimacy parameter between individuals, while the Y-axis represents the evolution time of the single social network model. In Figure 10, the X-axis represents the individual cognitive ability parameter and intimacy parameter between individuals, and the Y-axis represents the evolution time of the ISOE model.

In this experiment, when considering the impact of $\rho$ on the evolution process of opinions, we set different values for $\rho$: 0.0, 0.2, 0.4, and 0.6, while maintaining $\sigma$ as a constant value of 0.5. Similarly, when considering the impact of $\sigma$ on the evolution process of opinions, we set different values for $\sigma$: 0.0, 0.2, 0.4, and 0.6, while maintaining $\rho$ as a constant value of 0.5.

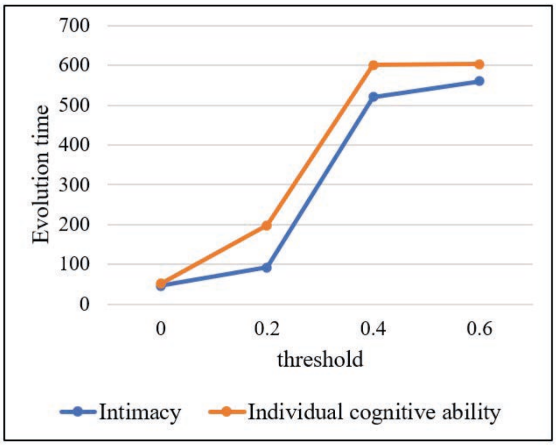


**Figure 9**. The influence of internal parameters on social networks.

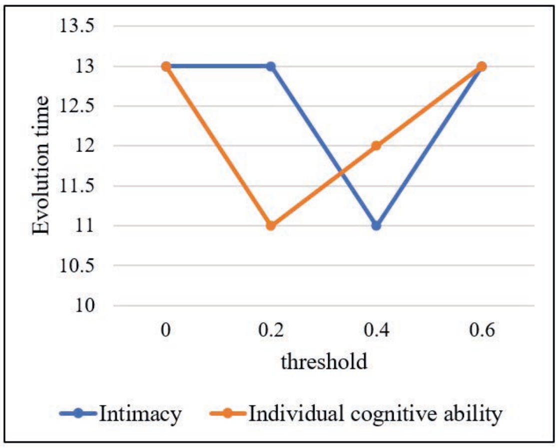


**Figure 10**. The influence of internal parameters on ISOE model.

From Figure 9, we can find that, in a single social network, the time for the evolution process of opinions to reach a stable state increases with ρ and σ. However, from Figure 10, we can find that, in the ISOE model, there is no obvious regular pattern in the time it takes for opinion evolution to stabilize.

The reasons for the above situation are as follows. ρ and σ assist individuals in filtering trusted individuals in their neighbors. The larger the values of ρ and σ, the stricter the filtering condition. This leads to a prolonged period for opinion evolution to achieve a stable state. Conversely, The smaller the values of ρ and σ, the looser the filtering condition. This leads to a shorter period for opinion evolution to achieve a stable state. In a single social network, only an evolution mechanism is needed to update individuals' opinions, and filtering trusted neighbor sets of individuals is an important work. Therefore, the role of ρ and σ are significant. However, in the ISOE model, two different opinion evolution mechanisms are used to update individuals' opinions, and filtering trusted neighbor sets of individuals is less important. Therefore, the role of ρ and σ are comparatively insignificant.

### 5.3 The influence of different initial opinion distribution on ISOE model

In this section, we conduct an experiment to validate the universality of our proposed model. In this experiment, different initial opinion distributions correspond to the manifestations of various events in reality. Three initial opinion distributions are applied: random distribution, bipolar distribution, and normal distribution. Random distribution applies to situations where the group has no bias toward a specific event, bipolar distribution applies to situations where the group holds two extreme attitudes toward a specific event, and normal distribution applies to situations where most people have a neutral attitude toward a specific event. In this section, the initial opinion distribution serves as a variable, while the remaining parameters remain constant. The experimental results are presented in Figure 11, and Figure 12, where the X-axis represents the initial opinion distributions and the Y-axis represents the evolution time.

From Figure 11, and Figure 12, we can find that, for all models, the time that opinion evolution reaches a stable state is the shortest under the case of a normal distribution of initial opinions, with random distribution slower and bipolar distribution the slowest. As a result, due to different opinion evolution rules, there are significant differences in the time it takes for opinion evolution. In conclusion, the ISOE model generally results in a shorter evolution time compared to the single social network model.

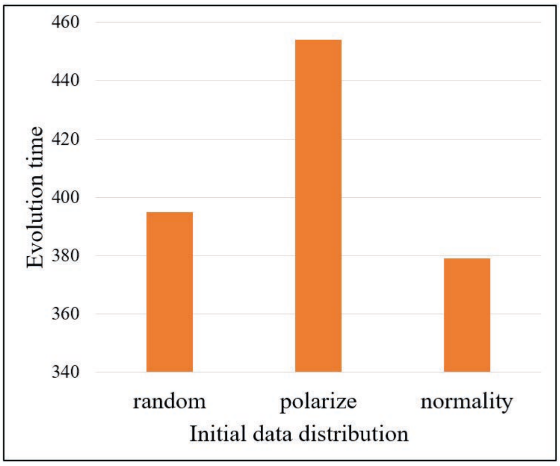


**Figure 11**. The influence of different initial opinion distribution on social network.

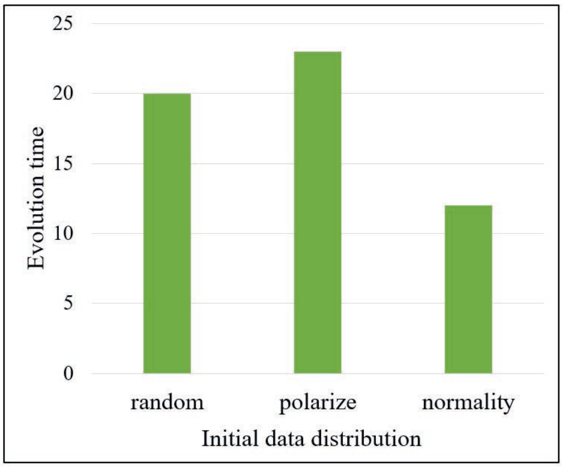


**Figure 12**. The influence of different initial opinion distribution on ISOE model.

In the case of a normal distribution of initial opinions, most people hold very similar opinions. During the evolution process of group opinions, individuals' opinions tend to converge towards consensus, resulting in the shortest time required for individuals to adjust their opinions. In scenarios with a random distribution of initial opinions, there is a significant dispersion in group opinions. Therefore, individuals require more time to adjust their opinions compared to when the initial opinions are normally distributed. Under the bipolar distribution of initial opinions, there is a significant difference in individuals' opinions, and individuals tend to maintain distance from each other rather than coming closer. As a result, it takes individuals the longest time to adjust their own opinions.

## 5.4 The effect of different initial opinion distributions on the effectiveness of guidance

In order to verify the influence of different initial data distributions on the guidance effect of the PDGM model, we take the initial data distribution as the independent variable, i.e., the proportion of extreme individuals among all the individuals of the group is set to be 0, 20%, 40%, 60%, 80%. The simulation results are shown in Figure 13 and Figure 14, in which the X-axis of Figure 13 represents the proportion of extreme individuals to all individuals in the group, and the Y-axis represents the number of evolutionary steps when the opinion guidance process reaches a stable state; the X-axis of Figure 14 represents the number of evolutionary steps when the opinion guidance process reaches a stable state, and the Y-axis represents the average opinion of the group in the opinion guidance process.

The bars in Figure 13 represent the specific values of the evolutionary steps when the opinion guidance process reaches a stable state, while the line graph illustrates the trend of these evolutionary steps. From Figure 13, it is evident that the presence of more extreme opinions within the group's initial stance prolongs the time required for the opinion guidance process to stabilize. In other words, the duration needed for the opinion guidance process to reach stability is directly proportional to the number of individuals holding extreme opinions. This phenomenon occurs because the proportion of positive opinions within the group significantly influences the interests of the more stubborn individuals. When the group contains a higher percentage of individuals with extreme opinions, the interests of the stubborn individuals decline at a slower rate, extending the period necessary for their opinions to change. Consequently, this delays the overall stabilization of the group's opinion. Therefore, the initial distribution of opinions within the group, or the starting state of the opinion landscape, is a crucial factor in determining the effectiveness and duration of the opinion guidance process. The more extreme the initial opinions, the longer it takes to achieve a guided consensus.

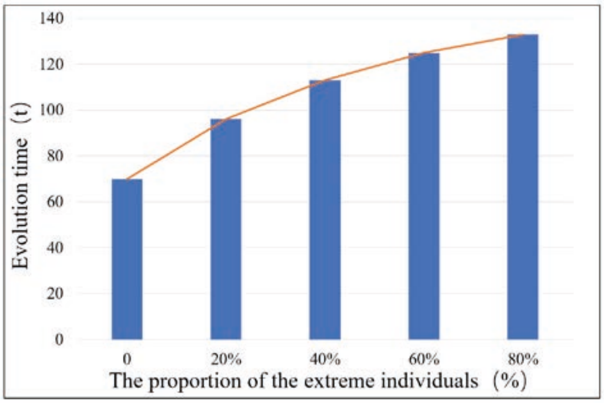


**Figure 13**. The effect of different initial data distributions on guidance effects.

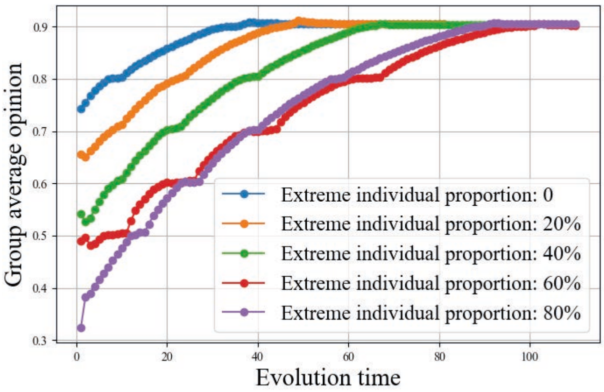


**Figure 14**. Changes in group average opinions with different initial data distributions.

The line graph in Figure 14 illustrates the changes in the group's average opinion under various initial data distributions. As shown inFigure 14, the different proportions of individuals with extreme opinions at the outset result in different initial average opinions. Consequently, the guidance process stabilizes at different times and rates. Specifically, a higher proportion of extreme individuals within the group leads to a longer and slower stabilization period for the guidance process. Conversely, a lower proportion of such individuals results in a quicker and more efficient stabilization. Therefore, in real-world public opinion scenarios, the greater the number of people holding negative opinions, the more challenging it is to guide the situation towards a desired outcome. On the other hand, a smaller number of people with negative opinions makes the guidance process easier and more effective.

## 5.5 The effect of the proportion of stubborn individual on the guidance effect

To evaluate the impact of varying proportions of stubborn individuals on the effectiveness of the PDGM model, we set the proportion of stubborn individuals as the independent variable. Specifically, we consider scenarios where the percentage of stubborn individuals within the group is 0%, 20%, 40%, 60%, and 80%. The simulation results are shown in Figure 15, in which the X-axis represents the proportion of stubborn individuals to all individuals in the group, and the Y-axis represents the number of evolutionary steps when the opinion guidance process reaches a stable state.

The bar graph in Figure 15 represents the evolutionary steps when the opinion guidance process reaches the stable state, and the line graph represents the trend of the evolutionary steps. From Figure 15, it can be seen that the higher the proportion of stubborn and extreme individuals in the group, the longer it takes for the opinion guidance process to reach a stable state. In other words, the time required for the opinion guidance process to reach a stable state is directly proportional to the number of stubborn individuals in the group. This is because one of the factors influencing the effect of opinion guidance on stubborn individuals is the opinion environment. Therefore, when the number of non-stubborn individuals is small and the number of stubborn individuals is large, the opinion environment changes slowly. Therefore, the perspectives of stubborn individuals can be guided for a longer period of time. Consequently, the time required for the opinion guidance process to reach a steady state is directly proportional to the number of stubborn individuals in the group.

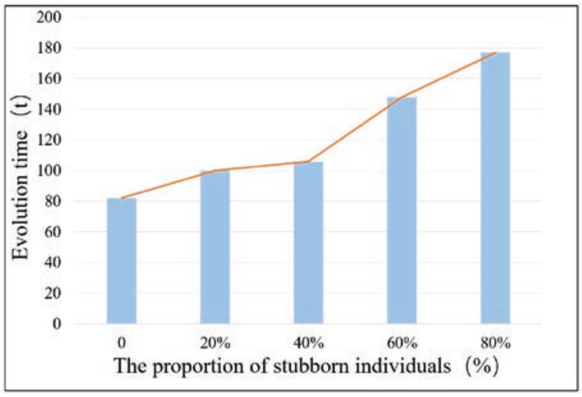


**Figure 15**. The effect of the proportion of the number of stubborn people on the opinion guidance effect

The line graphs in Figure 16 show how the average opinion of the group changes with different proportions of stubborn individuals. From Figure 16, it can be seen that due to the different proportion of stubborn individuals in the group, the initial average opinion of the group is different, and the time and speed of the guidance process to reach a stable state are also different. Specifically, when the proportion of stubborn individuals in the group is larger, the time for the guidance process to reach a stable state is longer and slower; when the proportion of stubborn individuals in the group is smaller, the time for the guidance process to reach a stable state is shorter and faster. Therefore, in real-life public opinion events, the more people with negative opinions and stubbornness, the more difficult it is to guide the event, while the fewer people with positive opinions and stubbornness, the less difficult it is to guide the event.

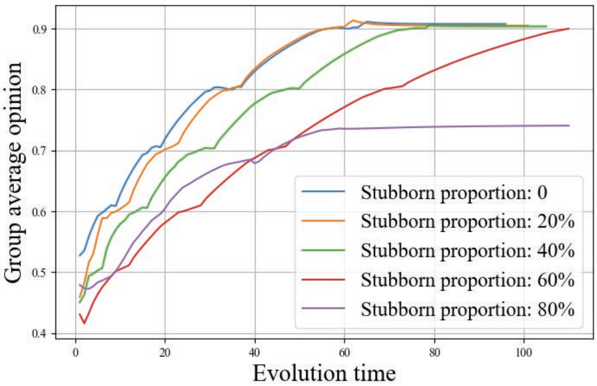


**Figure 16**. Trends in opinion environments with different proportions of stubborn people.

### 5.6 Influence of guidance ratio on guidance effect

In order to verify the influence of the guidance ratio on the guidance effect of the PDGM model, we take the guidance ratio as the independent variable in this section of the experiment, i.e., the ratio of the number of directly guided individuals among all individuals in the group is set to 40%, 50%, 60%, 70%, and 80%. The simulation results are shown in Figure 17, where the X-axis represents the value of the guidance ratio, and the Y-axis represents the number of evolutionary steps when the opinion guidance process reaches a steady state.

The bar in Figure 17 shows the number of evolutionary steps when the opinion guidance process reaches a stable state, and the line graph shows the trend of the evolutionary steps. From Figure 17, it can be seen that the more the number of directly guided individuals in the group, the shorter the time required for the opinion guidance process to reach a stable state. In other words, the time required for the opinion guidance process to reach a stable state is inversely proportional to the number of directly guided individuals in the group. The experiments show that the guidance strategy proposed in this work can have a good effect on the directly guided individuals.

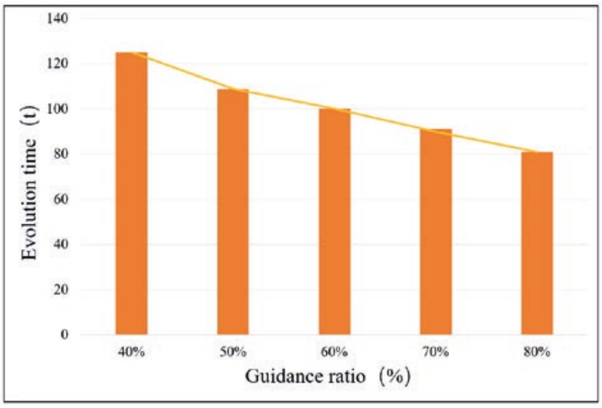


**Figure 17**. Influence of guidance ratio on guidance effect.

## Conclusion

The technology of opinion evolution and guidance is crucial for maintaining social stability, business development, etc. Currently, opinion dynamics are usually modeled in a social network, failing to consider the influence of information networks on opinion evolution and opinion guidance. To tackle the above issues, we propose an opinion evolution and guidance model based on social networks and information networks (EGSDCN), which includes two parts: an opinion evolution model (ISOE) and an opinion guidance model (PDGM).

For the ISOE model, we first design different opinion evolution mechanisms based on the differences in the interactions between individuals and between individuals and information; secondly, in the social network, ISOE proposes a method of filtering authoritative individuals based on individual heterogeneity, taking into account the differences in the degree of authority of individuals; and finally, based on the fact that social networks and information networks in reality are interconnected and interact with each other, this paper proposes a synergistic mechanism between information networks and social networks.

For the PDGM model, for the non-stubborn group, we design a linear function model to dynamically model the change process of the degree of stubbornness of individuals. This method is designed to effectively adjust individuals' stubbornness to specific opinions through subtle psychological guidance. For the stubborn group, we take into account not only the individual's initial opinion, the influence of their social network neighbors, and the impact of the information environment but also introduce an innovative factor: the adjustment of personal opinions in response to perceived losses of interest. To capture the dynamics of waning interest and the extent of opinion shifts, PDGM employs two trigonometric functions, providing a nuanced approach to understanding and influencing these processes.

Finally, a large number of simulation experiments are conducted in an artificial network environment, and the experimental results show that the PDGM model is not only more relevant to the actual situation of today's society but also better than most existing opinion guidance models in terms of performance.

The EGSDCN model has to some extent overcome the shortcomings of existing research on the evolution and guidance of opinions. However, when studying the influence of personality on opinion guidance, this study only considered two groups of people: stubborn and non-stubborn, and did not involve other personality types such as introverted and extroverted. In future research, it is necessary to further expand the classification of personality types to provide more targeted guidance for different groups and improve guidance effectiveness.

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