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The moderating effect of social network information diffusion on social participation among older adults

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Abstract This paper first introduces the concept of information diffusion in social networks and its characteristics, then clarifies the objectives and scope of social network data collection. Data related to user attention and follower counts were obtained through APIs, web scraping programs, and open data. To understand the impact of the complexity and uncertainty of information diffusion in social networks on the system, a dynamical model of information diffusion in social media networks under uncertain conditions was constructed based on system dynamics theory. Finally, the model is used to analyze the evolutionary trends of information diffusion in social networks and the moderating effects on older adults' social participation. The results show that there are strong interactive relationships between various variables in the dynamical system and information diffusion in social networks. Through the dynamical model, it is found that the evolution of numerical information characteristics reveals significant fluctuations in the network propagation speed of information within the first hour, which is related to the control capabilities of news media over information. Additionally, within the first hour, 72.72% of news media information dissemination networks had an average in-degree >1, under which conditions the social participation of the elderly was higher. Increasing the social participation of the elderly under conditions of high social network information diffusion can help maintain their cognitive function stability, playing an important role in their physical health.

Index Terms system dynamics model, social network, information diffusion, social participation, elderly

I. Introduction

With the widespread use of social media and the growing acceptance of the internet among the elderly, their social networks have also expanded [1], [2]. First, the dissemination of information through social networks has a positive impact on the social participation of the elderly [3], [4]. Social networks provide the elderly with avenues for communication and interaction with family members, friends, and community members [5], [6]. Through social media platforms, the elderly can maintain contact with distant relatives and friends, share the details of their lives, and convey their emotions [7], [8]. This communication and connection have a positive impact on the social participation of the elderly, making them feel cared for and valued, strengthening their social support networks, and promoting their willingness to actively participate in social activities [9]-[11]. Second, the diffusion of social networks among the elderly can also provide them with access to social resources [12]. Social media platforms offer a wealth of diverse information and resources. Older adults can use social networks to learn about various social activities, policies, and services [13], [14]. They can access information about social resources such as nursing homes, senior activity centers, and volunteer organizations through social networks, thereby better participating in social activities [15]-[17]. Additionally, social networks can provide older adults with opportunities for learning and entertainment, enriching their lives and enhancing their social participation [18], [19]. However, older adults' social networks also face challenges and barriers related to technology, spatial and temporal constraints, and physical health, which limit their communication and participation in society [20]-[22]. Therefore, measures need to be taken to help them overcome these barriers and improve the quality and breadth of their social networks. Only by continuously improving older adults' social networks can we better promote their social participation and enhance their quality of life [23]-[26].

Literature [27] constructed a conceptual framework based on action network theory and activity theory, incorporating factors such as information technology use and social participation. Through data analysis, it demonstrated that the use of information technology does not directly influence older adults' social participation. Literature [28] employed ordinary least squares regression and instrumental variables methods, using Chinese data, to examine the impact of internet use on older adults' social networks and its mediating role in social participation. The results indicated that internet use has a positive influence on older adults' social networks. Literature [29]

addressed two issues: “the association between internet use and older adults' social participation” and “the impact of internet use on social participation across different groups.” The results emphasized the significant impact of the internet on older adults' social participation, with frequent internet use leading to reduced social participation among women.

Literature [30] explores the impact of media usage, sociodemographic characteristics, and health variables on the elderly. The study findings indicate that the use of traditional media, digital access, and social media has a positive impact on the social participation of the elderly. Literature [31] aims to analyze the conceptual manifestation of information and communication technology (ICT) usage within the “Successful Aging 2.0” framework. The study finds that men are more likely than women to use ICT. Literature [32] emphasizes that ICT can enrich the lives of the elderly and examines the associations and relationships between computer/internet use, physical activity, and social integration before and after interacting with ICT. The results indicate that the elderly's social participation increases after becoming familiar with ICT. The above studies emphasize the impact of social network use, such as the internet and media, on the social participation of the elderly, revealing that social networks not only enrich the lives of the elderly but also effectively enhance their social participation.

Literature [33] investigated the moderating role of health characteristics on the relationship between psychological resources, community support, and social participation among the elderly. Based on key health indicators, multiple structural equation models were constructed. The results indicated that personal health significantly moderates the psychological and social compensation mechanisms influencing social participation. Literature [34] affirmed the positive impact of social participation on older adults and examined the types of social participation among extremely frail older adults and the factors influencing participation levels. Key factors influencing social participation include the decline in physical function among older adults and physical environmental factors. Literature [35] aims to clarify the ambiguity of the concept of social participation among the elderly. Based on a literature review, the defining attributes of the concept of social participation among the elderly include emphasizing community-based activities and interpersonal interactions. This study clearly presents the full scope of the concept of social participation among the elderly.

Literature [36] emphasizes the important role of social participation in improving the quality of life of the elderly and points out that social participation is influenced by various promoting or inhibiting factors. Through research, it is shown that the main obstacles to the social participation of the elderly, especially activities related to health, lie in costs and access. Literature [37] examines the impact of social participation (SP) on the health status of middle-aged and elderly Chinese individuals and adjusts for simultaneity and heterogeneity biases. Through survey analysis, it is pointed out that SP has a positive impact on mental health and activities of daily living. Literature [38] assessed the relationship between social support, general self-efficacy, and social participation. Based on questionnaire surveys, it pointed out that factors such as gender, educational attainment, and residential area are associated with social participation levels, emphasizing the significant role of social support and self-efficacy in social participation.

Literature [39] explored the impact of social participation on differences in mental health among urban and rural elderly in China. The analysis results indicated that social participation played an important role in enhancing cognitive abilities and mental health levels among both urban and rural elderly, with the impact on health being more pronounced among rural elderly. Literature [40] studied the relationship between social participation and the mental health of the elderly. Questionnaire survey results indicated that the mental health of the elderly is significantly related to social participation, but only physical and social performance show a significant positive correlation with social participation. Literature [41] compared the social participation status and barriers of elderly women and men by dividing Canada into different regions and population sizes, emphasizing that there are no substantial differences in the degree of social participation between women and men. Literature [42] aimed to assess the mutual relationship between the development trajectory of daily living ability impairments among the elderly and social participation. Survey results showed that elderly individuals with high levels of social participation were more likely to be categorized as having a stable trajectory in both daily living self-care abilities and daily living assistance activities. The above studies affirm the positive impact of social participation on the lives of the elderly, including promoting mental health and improving quality of life. At the same time, factors such as mental health, self-efficacy, and physical fitness interact with social participation.

This study takes social networks as its starting point, beginning with an overview of the concept of social networks to understand their overall characteristics. It then provides a brief summary of the characteristics of information diffusion within social networks and utilizes API interfaces and programming to collect large amounts of data. Subsequently, the study identifies the influencing factors within the information diffusion system of social media social networks and analyzes the relationships between system elements from three subsystem levels: the promotion level, the reception level, and the control level. Second, a causal relationship diagram and system flow

diagram of the entire system were constructed, and a dynamic model of the social media social network information diffusion system was established. The application effectiveness of this model in social network information diffusion was then simulated and analyzed. Finally, the evolutionary characteristics of social network information dissemination and its impact on the social participation of the elderly were explored.

II. System dynamics model based on social network information diffusion

II. A. Data collection methods for social network information diffusion

II. A. 1) Information Diffusion in Social Networks

Social Networking Services (SNS) [43]: These are social networks established online based on real-life interpersonal relationships, where users connect with others through shared interests, online activities, and information dissemination, forming a more complex social network structure. To some extent, these networks reflect users' real-life social relationships while also being modified to create a social circle that better meets their needs.

Social Network Information Diffusion: In the new era, social networks are built on relationships, relying on the network of connections between user nodes to firmly integrate users into online social interactions. Additionally, factors such as information characteristics, user preferences, network structure, and neighbor information exchange significantly influence the effectiveness of information dissemination.

II. A. 2) Social Network Data Collection Objectives and Scope

The data collection process for social networks in this study is primarily divided into the following stages: identifying the target, data collection, data preprocessing, and storage.

(1) Analysis of social networks

This paper investigates the impact of information diffusion in social networks on the social participation of older adults. Therefore, the specific differentiation of social networking sites is primarily focused on a specific social networking site—Weibo—as the research object, thereby enabling more targeted research on specific issues.

(2) User behavior on social media platforms

From the perspective of the occurrence of user behavior, posting and reposting are one-to-many relationships. The sender transmits information, which is received by the recipient, who then decides whether to further disseminate the information after consideration and judgment.

(3) Determination of Data Collection Objectives

Since this study focuses on user behavior within social networks, and Sina Weibo possesses certain unique characteristics, the study selects specific behaviors within Sina Weibo that can influence information diffusion and dissemination. For example, information posting, commenting, and reposting on Weibo will be specifically examined.

(4) Selection of Data Sample Scope

This paper believes that selecting user subgroup information to reflect the overall data situation is both scientific and realistic. Therefore, a sampling survey method is employed, using a “viral” data collection approach to obtain a representative subgroup for analysis, thereby deriving corresponding conclusions.

II. A. 3) Data collection methods

In terms of data collection, a combination of APIs, web scraping programs, and open data was employed to ensure that the data was as complete and representative as possible. This paper utilized web scraping to collect user names, number of followers, number of fans, and number of Weibo posts for a portion of users. For user relationship data, a combination of Weibo API interfaces and open data was used. The API interfaces used for data collection and their descriptions are shown in Table 1.

Table 1: Several API interfaces and their descriptions of data collection

Interface	Interface description
Friendships/followers	Get a list of user fans
users/counts	Number of fans, number of attention and microblogs
Statuses/user_timeline	Get users posted microblogs
Comments/show	Return a list of comments on a microblog based on the microblog ID
Statuses/repost_timeline	Get a list of tweets that are designated for microblogs
Statuses/count	Batch acquisition of the forwarding number of the specified microblogs
Statuses/show	Obtain single micro blog content according to micro blog ID

(1) Construction of social network topology maps

The construction of social network topology maps requires an understanding of the network interaction relationships between user groups in order to construct a relatively rigorous social network map. This paper uses the “keywords” and “tags” feature on Sina Weibo to identify a set of source users. The followers and subscribers of these source users are then collected as the next level of users. This process is repeated to capture followers and subscribers from this level, and so on, to obtain a substantial number of users as a sample.

(2) Acquisition of user behavior data

The process of obtaining users' followers and following lists is shown in Figure 1. By analyzing the number and timing of their posted microblogs, as well as the number of comments and retweets they generate, we can identify underlying behavioral patterns and assess their usability value. Additionally, since verified users and ordinary users differ in their microblog posting behavior, this paper collects data separately for these two groups to distinguish between them.

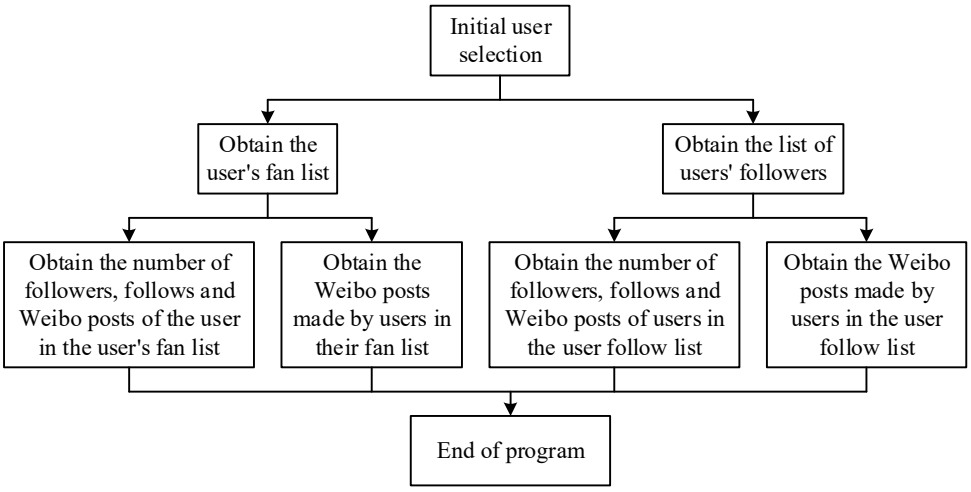

Figure 1: Flowchart for obtaining the user's fan and follower list

(3) Acquisition of data on the dissemination of popular Weibo reposts and comments

This paper primarily uses the dissemination of social network information as an example, including the reposting and commenting behavior triggered by this information, in order to subsequently control and guide related online public opinion. First, a web scraping tool is used to design a page scraping workflow diagram. The scraping tool then follows the steps outlined in the diagram to sequentially collect the required data and categorize it into database tables. The process for obtaining Weibo reposts and comments is shown in Figure 2. The entire process does not require manual collection of individual data items; instead, the data is collected automatically once the workflow is designed.

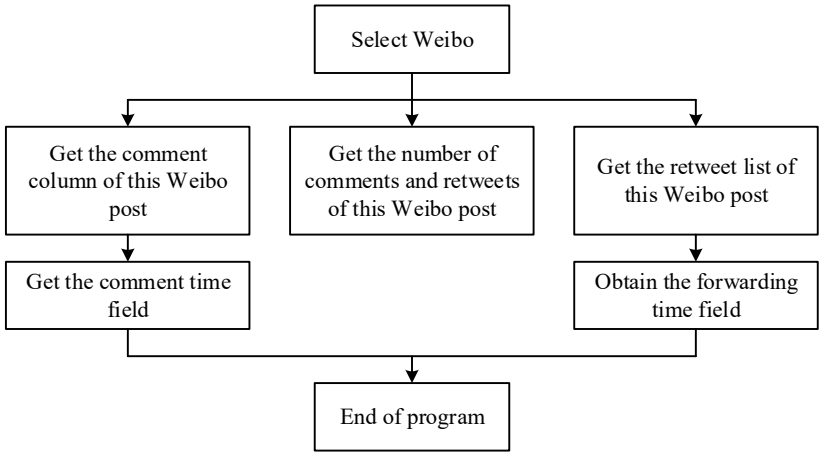

Figure 2: Flowchart for Obtaining the number of retweets and comments on Weibo

II. A. 4) Data Analysis

The user behavior data in social networks studied in this paper mainly includes two aspects: one is the user relationship topology map of social networks, and the other is the study of users' behavior in posting, reposting, and commenting on information. The analysis of these two aspects mainly uses SPSS software.

II. B.Modeling the dynamics of information diffusion in social networks

II. B. 1) Modeling Preparation

System dynamics theory [44] is an effective tool for studying changes in the dynamic behavior of an entire system by analyzing the causal feedback structure among various variables within the system. Therefore, before constructing a system dynamics model of information diffusion behavior in social networks, it is necessary to identify the influencing factors within each subsystem. Thus, clearly defining the system boundaries is of paramount importance in the process of constructing a system dynamics model. The issue studied in this section is the dynamic trend of information diffusion behavior in social networks. Therefore, “information heat” is used as the evaluation metric for the diffusion trend of social network information on social media. In social media, the dynamic system of information diffusion behavior in social networks is a dynamic process influenced by multiple factors. By analyzing and classifying these influencing factors, this section divides the social media social network information diffusion system into three subsystems: the promotion layer, the reception layer, and the control layer. The various factors within the system are interconnected and collectively influence the information heat of social networks.

II. B. 2) Model propagation mechanism

By analyzing the causal relationships among the influencing factors in the dynamic process of information diffusion behavior on social networks, we construct a causal relationship diagram of social participation among the elderly, thereby establishing a dynamical model of the social network information diffusion system. The causal relationships in the social information diffusion dynamical system are shown in Figure 3. Factors can be represented as nodes in the network, primarily divided into “cause” nodes and “effect” nodes, and the same node can serve as both a ‘cause’ node and an “effect” node. Multiple edges with common nodes can form a causal chain. When the first and last nodes of a causal chain are the same, it forms a causal loop with polarity (positive or negative), i.e., a feedback loop. At this point, the polarity of the feedback loop is also determined by the number of positive and negative causal relationships within the loop.

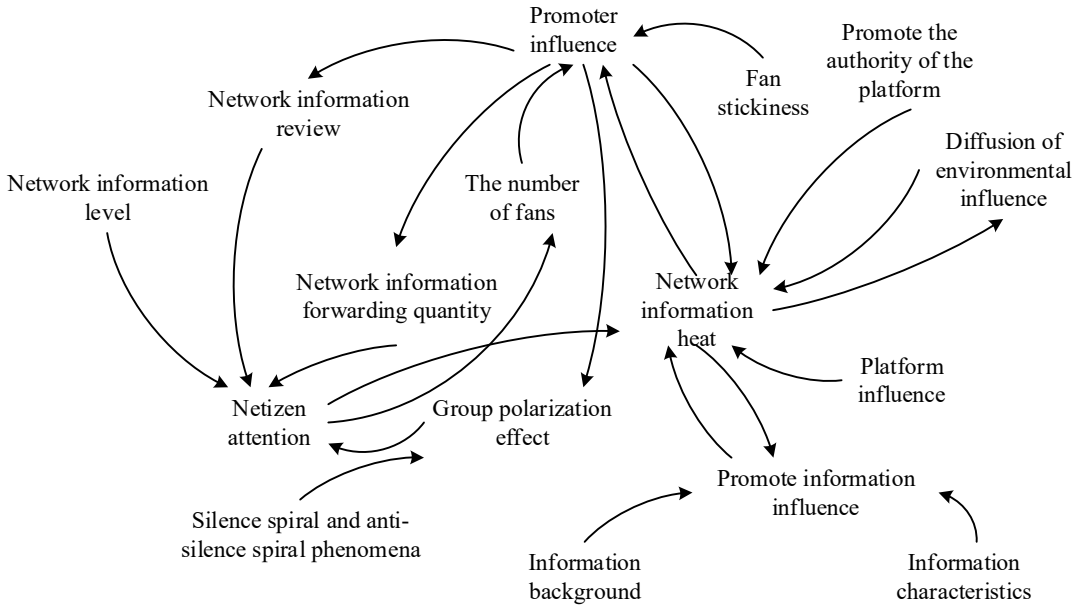

Figure 3: Causality of social information diffusion dynamics system

II. B. 3) System dynamics model construction

System flow diagrams are based on causal relationship diagrams, but with the addition of variable relationship settings, variable assignments, and numerical calculations. Therefore, system flow diagrams are quantitative analyses, causal relationship diagrams are qualitative analyses, and system dynamics is a theory that combines

quantitative and qualitative analyses. The dynamics of information diffusion in social networks are shown in Figure 4.

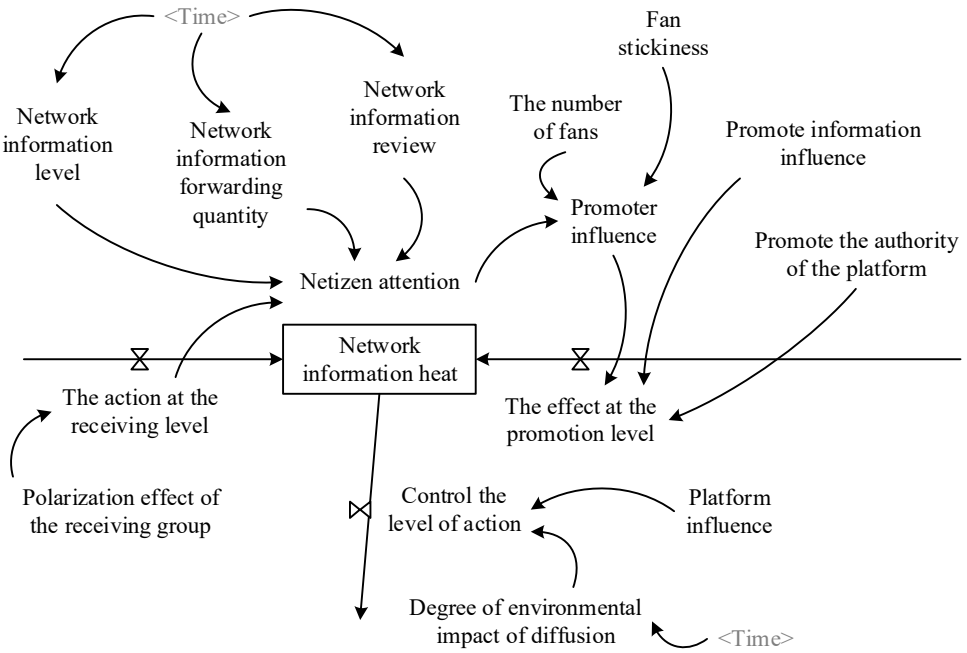

Figure 4: Social network information diffusion dynamics process

The variable relationship shown in the figure is:

$$\text{Netizen attention} = \begin{bmatrix} DELAY(\text{The number of likes for advertising information},1) \\ +DELAY(\text{The number of advertising information forwards},1) \\ +DELAY(\text{The number of comments on advertising information},1) \end{bmatrix} / 3 \quad (1)$$

Among these, netizen attention is the result of the combined influence of the number of likes, shares, and comments, and there is a delay. That is:

$$\begin{aligned} &\text{The action at the receiving level} = \text{Netizen attention} \\ &\times(1 - \text{According to the extreme effect response of the receiving group}) \end{aligned} \quad (2)$$

$$\begin{aligned} \text{Promoter influence} = {} &\text{Number of fans and fan stickiness} \\ &\times(1 + \text{Netizen attention}) \end{aligned} \quad (3)$$

$$\begin{aligned} &\text{The effect at the promotion level} = \text{Promote this influence} \\ &\times(1 + \text{Promote the influence of the product}) \\ &\times\text{Promote the authority of the platform} \end{aligned} \quad (4)$$

Since the spread of information on social networks is affected by environmental noise such as other network information or sudden events, the process by which it affects the spread of information on social networks is uncertain. Therefore:

$$\begin{aligned} &\text{Degree of environmental impact} \\ &\rightarrow \text{Degree of environmental impact} + \sigma \cdot \text{Noise} \end{aligned} \quad (5)$$

That is:

$$r \rightarrow r + \sigma \cdot noise \quad (6)$$

Let P_t be the diffusion environment influence at time t. If disturbances are not considered, its change can be described as follows:

$$\frac{dP_t}{dt} = rP_t \tag{7}$$

If noise is described as a Wiener process, the above equation can be replaced by:

$$\frac{dP_t}{dt} = rP_t + \sigma P_t \frac{dW_t}{dt} \tag{8}$$

In this case, noise is a normal random variable with an expected value of 0 and a variance of ∞, which means that the instantaneous rate of change of environmental impact dP_t / dt must always be infinite. That is:

$$\frac{dW_t}{dt} \sim N(0, \frac{1}{dt}) \tag{9}$$

Taking dC_t / dt as the noise term, an uncertainty environment influence model is then derived. Specifically:

$$\frac{dP_t}{dt} = rP_t + \sigma P_t \frac{dC_t}{dt} \tag{10}$$

Among them, C_t is a Liu process; and the noise term $\frac{d}{C_t}dt$ is an uncertain variable with an expected value of 0 and a variance of 1, i.e., $\frac{d}{C_t}dt \sim N(0,1)$.

The equivalent form of the above equation is:

$$dP_t = rP_t dt + \sigma P_t dC_t \tag{11}$$

One solution is:

$$P_t = P_o \cdot \exp(rt + \sigma C_t) \tag{12}$$

If the changes in the diffusion environment influence follow formula (10), then:

$$M\{P_t \geq 0, \forall t \geq 0\} = 1 \tag{13}$$

If the change in diffusion environmental influence follows formula (10), then the expected value of the first hit time when diffusion environmental influence reaches the λ level is:

$$E(t_\lambda) = \begin{cases} \int_0^{+\infty} \inf\{\alpha \mid \sup\limits_{0 \leq t \leq \kappa} P_t^\alpha \geq \lambda \mid d\kappa, & \lambda > P_0. \\ \int_0^{+\infty} (1 - \sup\{\alpha \mid \inf\limits_{0 \leq t \leq \kappa} P_t^\alpha \leq \lambda\}\})d\kappa, & \lambda \leq P_0 \end{cases} \tag{14}$$

Among them:

$$P_t^\alpha = P_0 \exp(rt + \frac{\sigma t\sqrt{3}}{\pi} \ln \frac{\alpha}{1-\alpha}) \tag{15}$$

By solving the ordinary differential equation:

$$dP_t^\alpha = rP_t^\alpha dt + \mid \sigma P_t^\alpha \mid \Phi^{-1}(\alpha)dt \tag{16}$$

We can obtain the following uncertain differential equation:

$$P_T = rP_T dt + \sigma P_T dC_T = rP_T dt + \mid \sigma P_T \mid \Phi^{-1}(\alpha)dt \tag{17}$$

There is an $\alpha -$ path:

$$P_t^{\alpha} = P_0 \exp(rt + \frac{\sigma t\sqrt{3}}{\pi} \ln \frac{\alpha}{1-\alpha}) \tag{18}$$

The equation for environmental impact is:

$$\begin{aligned} &\text{Diffusion of environmental influence} \\ &= P_0 \exp(r \times Time + \frac{\sigma \times Time \times \sqrt{3}}{\pi} \times \ln \frac{\alpha}{1-\alpha}) \end{aligned} \tag{19}$$

In this equation, r represents the expected impact of the environment on the diffusion of information in social networks, and σ represents the intensity of noise disturbance. According to the expert scoring method, $P_0 = 1, r = -0.6, \sigma = 0.3, \alpha = 0.8$.

$$\begin{aligned} &\text{The control level effect} = \text{platform influence} \\ &\times \text{diffusion environment influence} \end{aligned} \tag{20}$$

$$\begin{aligned} &\text{Advertising popularity} \\ &= INTEG \begin{pmatrix} \text{The action at the receiving level} \times \text{The receiving level acts on weights} \\ +\text{The effect at the promotion level} \times \text{The weight of the promotion level} \\ -\text{Control the level of action} \times \text{Control level action weight} \end{pmatrix} \end{aligned} \tag{21}$$

From the system dynamics model, it can be seen that the reception level, promotion level, and control level all have an impact on the diffusion of information in social networks. This paper argues that the popularity of information in social networks is the result of the combined effects of these three levels, and therefore the corresponding weights should be normalized. Using the expert scoring method, the weights of the three factors are 0.2516, 0.3824, and 0.3597, respectively.

II. B. 4) Model Parameter Settings

In the social media social network information diffusion dynamics system model, the number of followers, follower stickiness, promotional information influence, and promotional platform authority are all constants. Among these, promotional information influence is obtained through Weibo, and promotional platform authority is represented by user ratings. The specific calculation formula is as follows:

$$\text{The number of fans} = \text{the average number of fans of the promoter} \tag{22}$$

$$\text{Fan stickiness} = \frac{\text{cumulative number of likes}}{(\text{Amount of silks} \times \text{Number of messages})} \tag{23}$$

Based on the Weibo platform, through crawling and statistical analysis of relevant data, we can obtain the following results: the promoter has 10,000 followers, with a follower retention rate of 5% and a social network information diffusion influence of 0.65. The authority of the promotion platform can be obtained through expert scoring, which is 0.9.

II. C. Simulation of online public opinion diffusion based on system dynamics

II. C. 1) Changing public opinion sensitivity

This paper conducts a simulation test of public opinion sensitivity by increasing the public opinion sensitivity variable (MGD) by 20% and decreasing it by 20%. The impact of altering public opinion sensitivity on the diffusion of information in social networks is illustrated in Figure 5. The results indicate that if the sensitivity of the social network increases by 20% from its initial state, the diffusion of information in the social network will experience a significant increase; conversely, when public opinion sensitivity decreases by 20%, the diffusion of information in the social network will experience a slight decrease. This indicates that the variable public opinion sensitivity is an incentive factor for information diffusion in social networks. A decrease in its level does not have a significant weakening effect on information diffusion, but an increase in its level can lead to a multiplicative growth effect. This result also suggests that the weakening of public opinion information diffusion caused by a decrease in public opinion sensitivity is a gradual process, and if not properly guided, it may trigger a strong rebound.

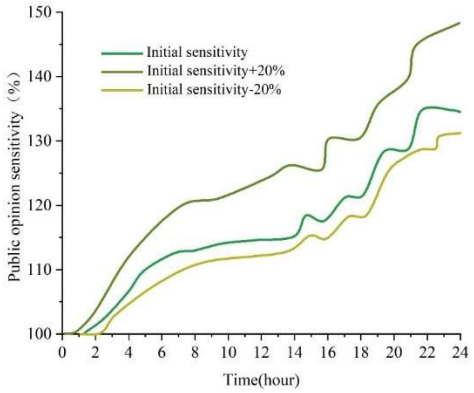

Figure 5: The impact of public opinion sensitivity on the spread of information

II. C. 2) Changing the activity level of the main body

To determine the relationship between the activity level of older adults and the diffusion of information on social networks, this study conducted experiments by increasing and decreasing the variable of activity level (HYD) by 20% respectively. The impact of changes in activity level on the diffusion of information on social networks is shown in Figure 6. The results indicate that if the activity level increases by 20%, the diffusion of information on social networks will slightly improve, while if the activity level decreases by 20%, the diffusion of information on social networks will experience a significant decline. This indicates that elderly individuals' activity levels are a protective factor for information diffusion in social networks. While an increase in activity levels does not significantly enhance information diffusion, a decrease in activity levels can lead to a multiplicative decline in information diffusion. This result also suggests that appropriately guiding the topics discussed in social networks and reducing the activity levels of elderly individuals in specific topics can significantly reduce information diffusion in social networks.

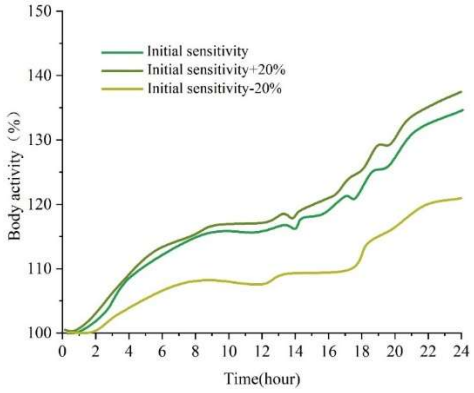

Figure 6: The effect of active activity on the spread of social network information

II. C. 3) Changing Media Influence

If the variable media influence (YXL) is increased by 20% and decreased by 20%, respectively, the impact of changes in media influence on the dissemination of online information is shown in Figure 7. According to the simulation results, regardless of whether media influence increases by 20% or decreases by 20%, the dissemination of information on social networks will experience significant fluctuations that are generally consistent with the direction of the change. This indicates that media influence exerts a relatively direct impact on the diffusion of information in social networks, and the diffusion of information in social networks is highly sensitive to changes in the variable media influence. This result also suggests that the authority and influence of communication media play a significant promotional role in the effective diffusion of information, and strengthening control over media influence can produce a notable effect in reducing the diffusion of information in social networks.

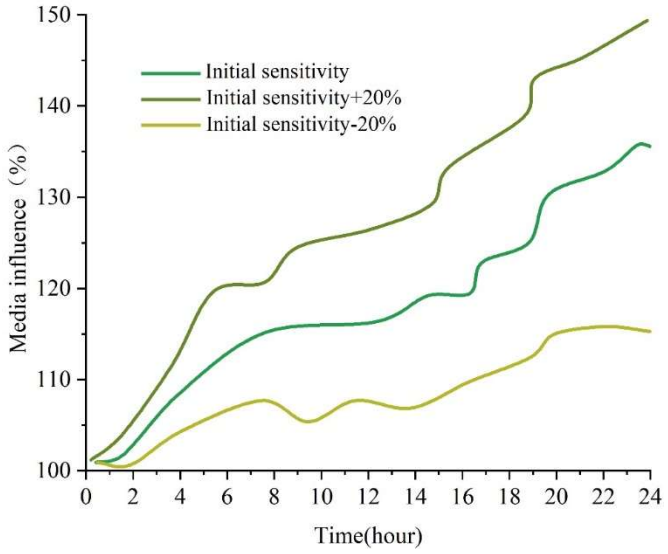

Figure 7: Influence of media influence on network information dissemination

II. C. 4) Changing audience engagement

If the audience engagement (CYD) of the target audience (the elderly) is increased by 20% or decreased by 20%, the simulation results showing the impact of changes in audience engagement on the diffusion of online information are shown in Figure 8. Whether audience engagement increases by 20% or decreases by 20%, the diffusion of social media information only exhibits a slight change consistent with the direction of the change. This indicates that audience engagement has a relatively indirect impact on the diffusion of information on social networks, and the diffusion of information on social networks is not sensitive to changes in audience engagement. This result also suggests that the impact of audience engagement on the diffusion of information on social networks is significantly lower than the impact of factors such as public opinion sensitivity and the activity level of public opinion entities.

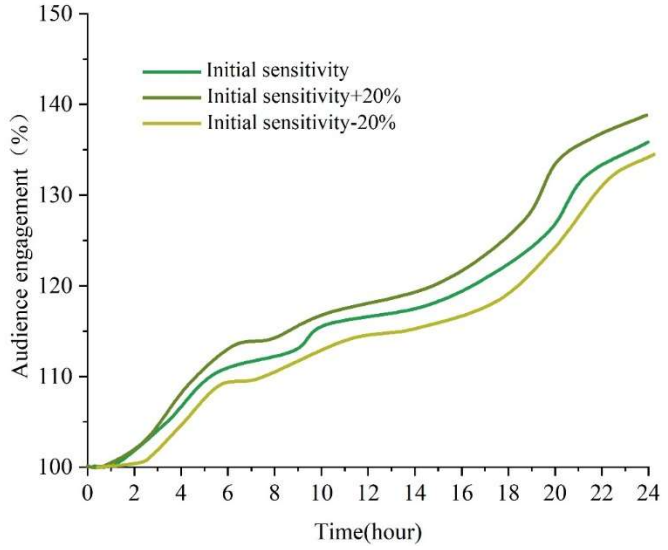

Figure 8: Impact of audience engagement on network information diffusion

III. The moderating effect of social network information dissemination on social participation among older adults

This section conducts an empirical analysis using the example of the “pension insurance incident” that occurred in 2024 and its regulatory effect on the social participation of the elderly through the dissemination of information on social media.

Using network analysis tools such as GEPHI and text processing tools such as ROST, we conduct a dynamic analysis of the information dissemination network from three dimensions: numerical characteristics, text

characteristics, and topological characteristics, to explore the evolutionary patterns of the network's regulatory effect on the social participation of the elderly through information dissemination.

III. A. Evolution of numerical information characteristics based on dynamic models

Numerical characteristics are a representation of the evolution of information dissemination networks, reflecting the quantitative changes in indicators during the evolutionary process of the network. They provide direction for in-depth exploration of the intrinsic characteristics and driving forces of the network. This section will utilize an information diffusion dynamics model to characterize the evolutionary process of network numerical characteristics based on three indicators: dissemination scale and speed, user engagement, and the dominant dissemination capabilities of news media.

III. A. 1) Scale and speed of dissemination

The propagation speed refers to the number of retweets increased per unit of time, and the sum of propagation speeds constitutes the propagation scale. By analyzing the dynamic changes in propagation speed, the critical time periods during the peak propagation phase can be further identified. The 11 key pieces of information related to the pension insurance incident, such as “elderly people, pension, insurance, pension amount,” etc., are named A1-A11 respectively. The hourly transmission speeds of the 11 information transmission networks are shown in Figure 9. It is evident that the transmission speeds of most information exhibit significant time sensitivity, decreasing over time. The transmission speed during the first hour accounts for a significant proportion of the transmission scale, indicating that the first hour is the most critical period for information transmission.

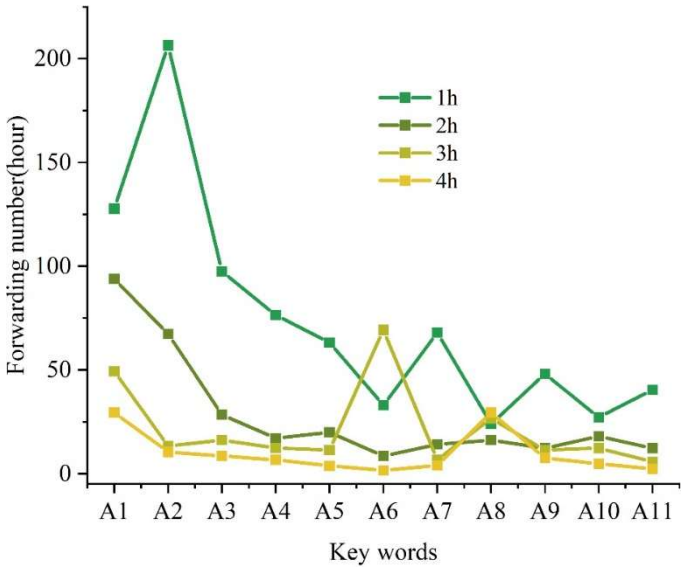

Figure 9: 11 information propagation network per hour propagation speed

To investigate the trend in propagation speed changes within the first hour, this paper further refines the time units to illustrate the minute-by-minute changes in propagation speed across 11 information propagation networks during the first hour. The minute-by-minute propagation speeds of the 11 information propagation networks are shown in Figure 10. As shown in the figure, during the first hour when information propagation is relatively fast, the propagation speed exhibits significant fluctuations and does not strictly decrease with time. News media information experiences its first noticeable peak in transmission speed within the first 10 minutes after publication. After a period of fluctuating fluctuations, the transmission speed of most information transmission networks gradually decreases at a slower rate. However, information transmission networks A3, A2, and A1 experience a second, more significant peak in transmission speed between 25 and 45 minutes, with the second peak having a higher peak value and longer duration, significantly driving the transmission of news media information within the first hour.

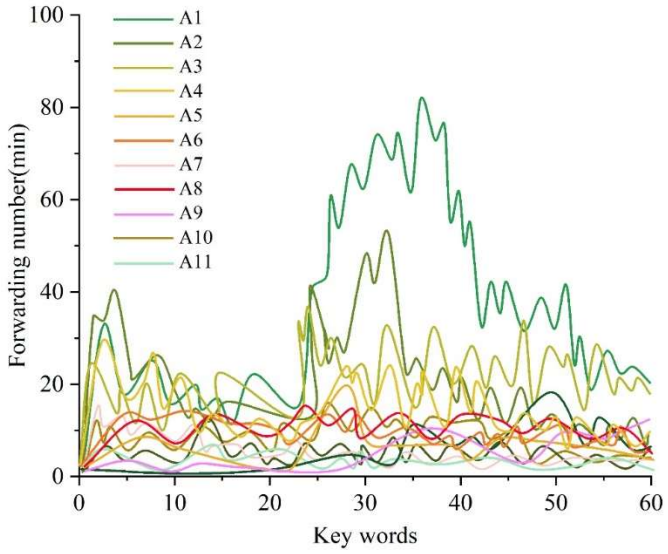

Figure 10: 11 information propagation networks per minute propagation speed

III. A. 2) Dominant capacity in news media dissemination

Since the information disseminated on the Internet is mainly news media-published information, this paper proposes the concept of news media dissemination dominance (DONA) to describe the dominant control that news media has over information in the process of information dissemination. The DONA formula is as follows:

$$DONA = \frac{out(p) + \sum outD(R_{nth})}{|E|} \tag{24}$$

Where P is the root node of news media information, and R_{nth} is the n th self-retweet node. DONA represents the ratio of the number of retweets triggered by news media to the total number of retweets. The higher the DONA, the stronger the news media's dominant ability to spread information.

The differences in DONA values across 11 information dissemination networks are shown in Figure 11. As shown in the figure, except for networks A1, A2, and A3, which exhibit a slight increase in DONA during the peak dissemination period, the DONA values of the remaining 8 information dissemination networks all show a declining trend, with networks A11 and A10 exhibiting a particularly significant decline in DONA.

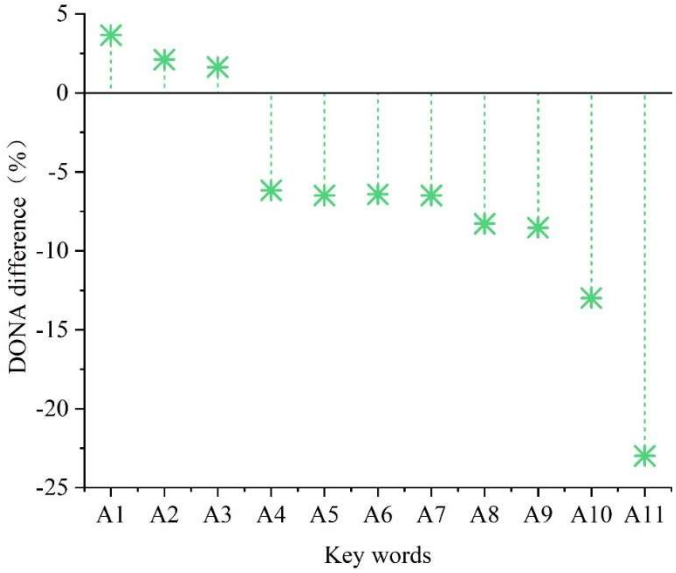

Figure 11: 11 information propagation network DONA change difference

III. A. 3) Social participation of older adults

This paper uses the average in-degree of the network to characterize the social participation of the elderly. If the average in-degree is less than 1 or equal to 1, the social participation of the elderly in the information dissemination process is low. If the average in-degree is greater than 1, the social participation of the elderly in the information dissemination process is high. The trend in the number of information dissemination networks across different average in-degree intervals is shown in Table 2. As shown in the table, within the first hour, 72.72% of news media information dissemination networks had an average degree >1, indicating a high level of social participation among the elderly. Subsequently, the number of networks in the average degree ≤1 interval decreased, while the number in the average degree >1 interval increased, resulting in an overall upward trend in social participation among the elderly across the network. That is, as time progresses, the level of social participation among the elderly in news media information dissemination networks gradually increases.

Table 2: Information dissemination network number change trend

Time(hour)	1h	2h	3h	4h
Average entry <1	1	1	1	1
Average entry =1	2	1	1	1
Average entry >1	8	9	9	9

III. B. Empirical analysis of the moderating effect of information diffusion on social participation among older adults

The study population for this section consists of data from the China Longitudinal Health and Retirement Study (CLHLS) conducted between 2005 and 2014, with a sample size of 5,000 individuals (2,493 men and 2,507 women), and an average baseline age of 75.4 years.

Cognitive function: The Mini-Mental State Examination (MMSE) was used to assess cognitive function in older adults. The MMSE includes information related to five dimensions: orientation, memory, attention and calculation, recall, and language, comprising 24 questions with a total score of 30 points.

Social participation: Social participation is assessed using five items: current marital status, living arrangements, ability to receive assistance when facing difficulties, presence of close friends, and participation in social activities. The social participation score is the sum of the scores for these five questions, ranging from 0 to 5 points, with higher scores indicating greater social participation.

The study participants were divided into three groups based on their social participation scores: low, moderate, and high social participation, corresponding to scores of 0–1, 2–3, and 4–5 points, respectively.

III. B. 1) Cognitive Change Trajectories in Older Adults

Based on the model screening criteria, this study progressively identified a linear and nonlinear combination of three types of social network information diffusion that effectively describes the trend of cognitive function levels in the elderly as social network information diffuses. The cognitive change trajectories of the elderly are shown in Figure 12. Among them, 4,250 (85%) elderly individuals were classified into the cognitive stability group: this group of elderly individuals had basically normal cognitive function that remained stable. 525 elderly individuals (10.5%) were classified into the slow cognitive decline group: these elderly individuals had baseline cognitive function that was basically normal but subsequently declined slowly. 225 elderly individuals (4.5%) were classified into the rapid cognitive decline group: these elderly individuals had baseline cognitive function that was significantly lower than the other two groups and declined rapidly.

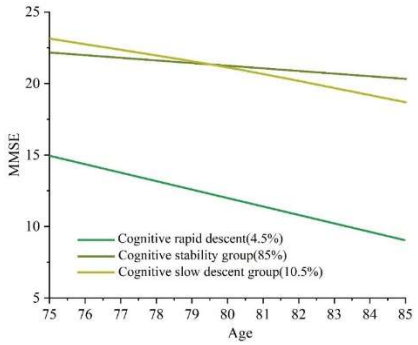

Figure 12: Cognitive changes in the elderly

III. B. 2) Comparison of baseline characteristics between different cognitive function groups

The results of the comparison of baseline characteristics among different cognitive change trajectories are shown in Table 3. There were statistically significant differences ($P < 0.05$) between different cognitive function groups in terms of age, BMI, social participation score, baseline MMSE, gender, educational attainment, smoking status, drinking status, and activities of daily living.

Table 3: Comparison of baseline characteristics of different cognitive changes

Project		Cognitive function change trajectory			Statistical value	P
		Stable group	Slow descent group	Rapid descent group		
Age (year)		74.71	84.56	76.79	26.1905	0.0000
BMI (kg/m2)		0.84	19.34	23.92	9.7314	0.0000
Social participation scores		3.75	3.24	3.34	121.0418	0.0000
Baseline MMSE		27.51	23.34	19.35	592.9602	0.0000
Gender	Man	2249.09	139.91	44.92	0.0000	0.0000
	Female	2086.9	399.04	123.07		0.1599
Domicile	Town	2734.19	381.93	125.9	2.1055	0.0000
	Countryside	1601.96	156.76	41.89		0.0000
Education degree	Llliteracy	2349.96	96.03	34	80.7456	0.0299
	Nonilliterate	1986.06	442.91	133.96		0.0000
Smoking condition	Never smoking	1210.04	77.93	37.02	—	0.0000
	Past smoking	581	41.94	14.11	4.6814	0.1799
	Smoking now	2544.83	418.94	116.92	34.7013	0.0000
Drinking condition	Never drink	1133.07	81.8	41.94	21.1573	0.0804
	Alcohol consumption	461.88	45.11	17.02	1.7101	0.0000
	Drinking now	2740.96	411.95	108.99	25.091	0.7123
Regular exercise	Yes	1585.04	138.03	31.15	20.021	0.0000
	No	2750.9	401.09	137.11		0.0000
Social participation	Low	53.13	16.94	10.12	0.0831	0.0103
	Medium	1326.94	317.09	84.97	76.9612	0.0096
	Height	2956.06	205.04	73.06	76.8284	0.0601

III. B. 3) The relationship between social participation and cognitive change trajectories

Reference group = cognitive function stable group; Model 1 is the unadjusted model; Model 2 adjusted for age, gender, BMI, place of residence, educational attainment, smoking status, drinking status, physical activity, and activities of daily living; Model 3 further adjusted for baseline cognitive level on top of Model 2.

The association between social participation and cognitive change trajectories is shown in Table 4. The “cognitive stability group” was selected as the reference group. Compared with older adults with low baseline social participation, high social participation was associated with a reduced risk of both slow cognitive decline and rapid cognitive decline patterns (OR = 0.4905, 95% CI: 0.2384–0.9217; OR = 0.2316, 95% CI: 0.1103–0.4598). Compared with Model 3, the association between high social participation and the slow decline trajectory of cognitive function disappeared, while the association with the rapid decline trajectory of cognitive function weakened but remained statistically significant (OR = 0.3921, 95% CI: 0.1824–0.9508); moderate social participation was not associated with cognitive decline trajectories ($P > 0.05$).

Table 4: The association between social participation and cognitive changes

Social participation of the elderly		Low	Medium	Height
Slow descent group	Model 1	1.0000	0.7612(0.435,1.329)	0.2315(0.1407,0.3892)
	Model 2	1.0000	0.6502(0.317,1.208)	0.4905(0.2384,0.9217)
	Model 3	1.0000	0.7435(0.1653,0.7289)	0.6037(0.3306,1.1729)
Rapid descent group	Model 1	1.0000	0.3309(0.1624,0.7401)	0.1325(0.0684,0.2799)
	Model 2	1.0000	0.3887(0.1702,0.8613)	0.2316(0.1103,0.4598)
	Model 3	1.0000	0.6288(0.2719,1.5302)	0.3921(0.1824,0.9508)

IV. Conclusion

This paper constructs a diffusion dynamics model for information dissemination in social networks based on system dynamics theory and uncertainty theory. It also analyzes the application effectiveness of this model in regulating the social participation of the elderly.

(1) System internal variables such as public opinion sensitivity, subject activity, media influence, and audience participation have a strong interactive relationship with information dissemination in social networks and exert a significant overall influence on the latter.

(2) The majority of information exhibits significant time-sensitivity in its online dissemination speed, which decreases over time. During the first hour, the dissemination speed of information fluctuates significantly, with 72.72% of news media information having an average in-degree >1 in the dissemination network, indicating higher social participation among the elderly. Additionally, the dominant role of news media in information dissemination is time-sensitive, with their control over information weakening and dispersing over time.

(3) High social participation is a protective factor against cognitive decline in the elderly. Maintaining normal cognitive function in the elderly and achieving healthy aging should be achieved by encouraging the diffusion of information through social networks.

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