

An Empirical Study on the Social Media False Information Dissemination Model Based on AI Confrontation Mechanism

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Abstract: This article takes false information in social media as a research case to explore the influence mechanism and action path of users' information verification behavior, aiming to enhance the public's ability to distinguish online information and promote the self-purification of the online environment. This study, based on the Fine Processing Possibility Model (ELM), combined with questionnaire surveys and structural equation models, constructs a model of the influence mechanism of social media users' false information verification behavior, and conducts empirical tests on the relevant influencing factors. This research can provide a reference for the management of social media platforms and the prevention of false information by users. Using only one modal discriminator cannot fully exploit the invariance between modalities, thus limiting the accuracy of cross-modal retrieval. This study innovatively constructs a cross-modal feature alignment framework based on dual-channel all-modal encoders and adversarial learning. This model adopts a parallel architecture design, featuring two feature encoding channels: visual and text. It maps heterogeneous data to a unified representation space through a deep neural network. During the model optimization process, we embed a classification and discrimination module in the hidden layer of the feature extraction network and adopt an adversarial training strategy for multi-objective optimization, so that the obtained shared feature space simultaneously possesses: 1) cross-modal semantic consistency; 2) Modal invariant feature expression ability. The experimental results show that an individual's emotional tendency and risk perception level can significantly affect their information discrimination behavior patterns. These two psychological factors constitute the core dimensions of users' information verification decisions.

Keywords: AI-generated adversarial mechanism social media; all-modal autoencoder false information; fine processing possibility model

1 INTRODUCTION

In the social media information ecosystem, users, as the core subjects of information dissemination, have not yet systematically studied their verification decision-making mechanisms and influencing factors when facing suspicious information. An in-depth exploration of the influencing factors of this behavior is of great significance for curbing the spread of false information and promoting the healthy development of the online information ecosystem. At present, academic research on user information behavior mainly focuses on dimensions such as information dissemination, adoption, search and response [1], while specialized studies on false information verification behavior are relatively scarce and mostly limited to the analysis of "information verification" in specific contexts. Existing research has found that in the context of news dissemination, the sharing motivation, risk perception ability, reliability assessment of information sources, and dissemination willingness of information disseminators jointly affect the verification behavior of users [2]; Cross-cultural comparative studies have shown that the characteristics and types of information quality significantly influence the sharing and verification decisions of users in different countries [3]; Research based on the cognitive needs theory reveals that educational level regulates the relationship between cognitive needs and verification behavior, and the impact of information credibility on users with different educational backgrounds varies [4]. Experimental research has confirmed that users' subjective judgment of the authenticity of information will directly affect their willingness to verify [5]. Quantitative analysis reveals that network usage experience, information retrieval ability and verification attitude significantly predict users' self-efficacy towards misinformation [6]. Looking at the existing research, it mainly presents three characteristics: First, the research scenarios are concentrated in specific

fields such as news dissemination, social platforms and mobile terminals. Second, in terms of methodology, empirical analysis and model verification are mostly adopted. Thirdly, the research conclusions have significant implications for understanding user verification behaviors. However, these studies have not yet established a systematic theoretical framework for influencing factors, especially the verification behavior mechanism in the special communication environment of social media still needs in-depth exploration.

The human brain's perception of external things is produced by the combined action of multiple sensory organs. This is because the comprehensive information formed by the combination of data from different modalities can better reflect events and contents in the real world. However, the heterogeneity gap between the distributions of data from different modalities makes it extremely difficult for artificial intelligence technology to fully simulate the human brain to process it. Cross-modal feature association is aimed at breaking through this heterogeneity gap to establish semantic connections among data of different modalities. Specifically, it first needs to map the data of different modalities to a certain common subspace to obtain the corresponding common features. In this subspace, the data features of different modalities can be directly measured for similarity, thereby breaking through the heterogeneity gap existing among the data of different modalities. Then, the association between the data features of different modalities is established from the semantic level, making it discriminative in semantics and consistent in modality. Essentially, cross-modal feature association is a process of data feature learning and distribution fitting. Compared with traditional deep learning models, GAN has a more powerful ability in feature learning and distribution fitting, which enables it to reconstruct data features within modalities and data distribution between mixed modalities. Therefore, this paper holds that adopting the generative adversarial

mechanism is an effective approach for cross-modal feature association.

The necessity of studying the dissemination patterns of false information on social media lies in its ability to reveal the evolution laws and diffusion mechanisms of false information, providing a scientific basis for building a timely and effective governance system, and thereby resisting its continuous erosion of public security, social trust and the democratic process. This is an urgent need to maintain a clear and clean cyberspace and ensure the healthy development of society. This study focuses on the discrimination behavior of users towards suspicious information in the social media environment. Based on the framework of fine processing possibility theory and combined with the structural equation modeling method, it systematically examines the internal driving factors and their mechanism of action for users to implement information verification, aiming to provide a theoretical basis for building a collaborative governance system of false information with user participation. The information verification behavior referred to in this study specifically means a series of verification activities carried out by social media users to confirm the authenticity of suspicious information when they come into contact with it. It mainly includes but is not limited to the following forms: (1) Verifying online information through search engines; (2) Consulting relevant authoritative materials; (3) Discussing and verifying with members of the social relationship network; (4) Proactive verification behaviors such as consulting and verifying with domain experts. This operational definition emphasizes the subjectivity and initiative of users in the process of information dissemination, highlighting their crucial role in the discrimination of information authenticity.

2 RELATED WORK

In recent years, deep generative adversarial networks have made breakthrough progress in the field of cross-modal feature learning [7]. Their unique adversarial game mechanism provides a brand-new optimization paradigm for cross-modal feature extraction and association learning. In the field of cross-modal retrieval research, several innovative models have emerged in the academic community: The ACMR (Adaptive Multimedia Communication Routing) model [8] pioneered the construction of an adversarial learning framework based on modal discriminant networks. This network realizes the dynamic game process between feature extractors and discriminators by introducing a gradient inversion layer [9]. Specifically, the feature extractor generates a shared feature representation with high modal invariance by continuously optimizing network parameters, in order to maximize the confusion of the discriminator's judgment; Meanwhile, the discriminator continuously enhances its modal recognition capability, attempting to accurately distinguish the feature sources of different modalities. This ingenious adversarial mechanism not only effectively eliminates the distribution differences between modalities but also retains the semantic discriminability of features. This model also innovatively designs a semantic classification module, ensuring the discriminative performance of shared features in the semantic space

through supervised learning. The further developed CMGANs framework [10] proposed a modal-specific discrimination strategy. In text modal processing, this model uses text features as positive samples and image features as negative samples for adversarial training. It is particularly worth noting that this framework innovatively integrates a generative adversarial mechanism in the data reconstruction stage, significantly enhancing the accuracy of semantic representation through an adversarial reconstruction process. The GXN model [11] has made significant innovations at the feature embedding level. It deeply integrates the adversarial learning concept into the cross-modal feature embedding process, achieving multi-level collaborative learning of global abstract features and local semantic features. This fine-grained feature learning approach greatly enhances the accuracy of cross-modal associations. The more complex MASLN architecture [12] adopts an innovative idea of dual-network collaborative design: its cross-modal reconstruction network uses semantic labels as auxiliary information and minimizes the distribution differences between modalities through a carefully designed reconstruction loss function; Meanwhile, its modal semantic adversarial network ensures the modal consistency of the feature space through adversarial training. The newly proposed UCH model [13] has pushed research to a new height. It creatively integrates the idea of cyclic generative adversarial [14] with cross-modal hash algorithms, constructing a dual optimization architecture that includes an outer loop network and an inner loop network. Among them, the outer loop network focuses on learning high-quality shared feature representations, while the inner loop network is responsible for generating reliable hash codes. This innovative dual adversarial optimization mechanism significantly enhances the accuracy and robustness of cross-modal data association through an end-to-end training approach.

Based on the theoretical framework of the Elaboration Likelihood Model (ELM), this study deeply explores the verification behavior mechanism of social media users for suspicious information. This theoretical model was proposed by social psychologists Petty and Cacioppo in the 1980s [15]. Its core viewpoint holds that the influence of information on user behavior is achieved through the mediating variable of attitude change. According to this model, there are two differentiated paths for users to process information: One is the Central Route, which is manifested as users conducting systematic analysis and in-depth thinking on the information content. This process requires a considerable investment of cognitive resources and time costs. The second is the Peripheral Route, which refers to the situation where users rely on heuristic cues for quick judgment, and their cognitive input is relatively small [16]. Due to the essential difference in processing depth, the attitude changes formed by the central path have higher stability, persistence and predictability, while the attitude changes produced by the marginal path are more temporary and context-dependent. In the field of information behavior research, the dual-path model has been widely applied to explain users' information search and adoption behaviors [17, 18]. Existing research indicates that information quality (central path factor) and source credibility (marginal path factor) jointly influence

users' information adoption decisions [19, 20]. The intensity of users' information search is significantly positively correlated with their tendency towards fine processing. This study extends and applies this theoretical framework to the analysis of users' false information verification behavior in the social media environment. Specifically, when users are exposed to suspicious information, they will form differentiated attitude responses based on their personal knowledge reserves and situational factors, including authenticity assessment at the cognitive level and emotional responses at the emotional level. This model not only reveals the action paths of influencing factors at different levels, but also explains the differences in cognitive processing in users' verification behavior decisions, providing theoretical guidance for the information governance of social media platforms.

Based on the theoretical framework of the Fine Processing Possibility Model (ELM), this study divides the influence mechanism of social media users' information verification behavior into two key paths: the central path and the marginal path. These two paths shape users' attitude tendencies towards suspicious information in different ways, and thereby determine their final verification behavior decisions. In terms of the division of attitude dimensions, existing studies generally adopt the two-dimensional structure of emotion-cognition to predict user behavioral intentions [21, 22]. Among them, the intergroup emotion theory further emphasizes that individual behavior is simultaneously driven by both emotional preferences and rational cognition [23, 24]. Specifically, the emotional dimension reflects the subjective emotional experience that users have in response to information stimuli, featuring immediacy and intuitiveness. The cognitive dimension, on the other hand, reflects users' objective assessment of the value of information and demonstrates their rational judgment process. Considering the unique entertainment attributes of social media platforms and the potential risk characteristics

of false information, this study particularly deconstructs users' attitudes towards suspicious information into two key dimensions: the first is emotional response, that is, the emotional fluctuations and psychological feelings that users experience when exposed to information; the second is risk awareness, which refers to the user's alertness to the potential hazards of information and their risk assessment. Based on this theoretical framework, this study will construct an influence model of social media users' false information verification behavior from three interrelated levels: Firstly, analyze the differentiated influence mechanisms of the central path and the marginal path on users' attitudes; Secondly, explore the psychological process of user attitude formation. Finally, the predictive effect of attitude factors on information verification behavior is revealed.

3 CROSS-MODAL RETRIEVAL INTEGRATING ALL-MODAL AUTOENCODERS AND AI GENERATIVE ADVERSARIAL MECHANISMS

3.1 Generative Model

In view of the limitations of existing generative adversarial networks in cross-modal retrieval, this study proposes a cross-modal retrieval method (FA-GAM) that integrates the all-modal autoencoder and the generative adversarial mechanism. Existing methods usually only adopt a single modal discriminator, which makes it difficult to fully extract the common features among modalities, thereby affecting the retrieval accuracy. To solve this problem, FA-GAM adopts a dual-branch generative model structure, which includes image and text full-modal autoencoders (GI, GT) and classifiers (C). Unlike traditional autoencoders, all-modal autoencoders can not only reconstruct the features of their own modes but also generate cross-modal feature representations, thereby more effectively mining the correlations between modes, as shown in Fig. 1.

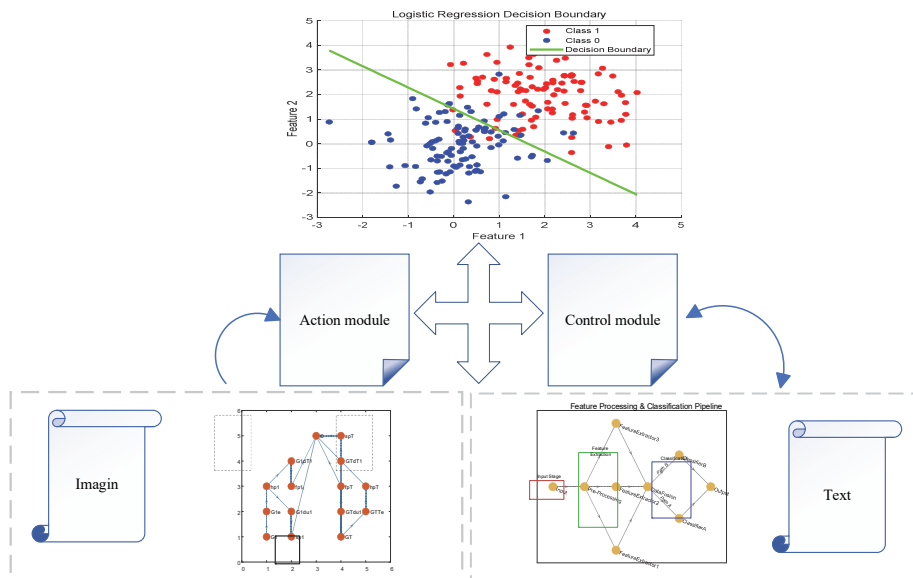


Figure 1 Structure diagram of FA-GAM

To ensure that image and text modal data can still maintain their original semantic discriminative characteristics after being mapped to the common feature

space, this study innovatively designed the cross-modal classifier module C. This classifier is embedded in the middle hidden layer position of the dual-channel

full-modal autoencoder architecture. Its main function is to map the feature representations of heterogeneous modalities (visual and text) to a unified semantic category space. In terms of specific implementation, we have constructed a classifier structure based on deep neural networks and optimized its parameters through supervised learning. In terms of the design of loss functions, we have proposed the semantic discriminative loss function. The core design concept of this loss function is to ensure that in the common feature space: (1) cross-modal samples of the same semantic category have highly similar feature distributions through the dual optimization goals of maximizing the inter-class distance and minimizing the intra-class distance; (2) The sample features of different semantic categories can be clearly distinguished; (3) The discriminative relationship of the original modal data is completely retained during the feature space transformation process. This design not only solves the semantic preservation problem in the cross-modal feature alignment process, but also significantly improves the accuracy and reliability of the final retrieval results.

$$L_{\text{dis}}(W_{\text{dis}}) = \frac{1}{n_{\text{train}}} \|W_{\text{dis}} H^I - Y\|_F + \frac{1}{n_{\text{train}}} \|W_{\text{dis}} H^T - Y\|_F \quad (1)$$

Here, W_{dis} represents the parameter of C , F represents the Frobenius norm, H^I represents the embedded feature matrix of the images in the training set in the common space, and H^T represents the embedded feature matrix of the text in the training set in the common space. Y represents the category label matrix of sample pairs in the training set. By minimizing $L_{\text{dis}}(W_{\text{dis}})$ to supervise the training of C , the network can learn the semantic discriminative information contained in the category labels and retain it in the public space.

Intuitively, the distance between the embedded features of similar samples in different modalities in the common space should be small, while the distance between the embedded features of unpaired samples in the common space should be large. To eliminate the differences between modalities, the distances of all image-text to feature representations should be minimized as much as possible. This chapter defines the Semantic consistency Loss Function L_{inv} , which uses Euclidean distance to measure the differences between embedded features of similar samples of different modalities.

$$L_{\text{inv}}(W_{\text{inv}}) = \frac{1}{n_{\text{train}}} \|H^I - H^T\|_F \quad (2)$$

Here, W_{inv} represents the parameter set of G_{Ie} and G_{Te} . By minimizing $L_{\text{inv}}(W_{\text{inv}})$, the embedding features of similar samples in different modalities are aligned as much as possible, and the differences existing between different modalities are effectively reduced.

In summary, the generative model loss function L_{gen} is defined, which is represented by the reconstruction loss function, the semantic discriminative loss function, and the semantic consistency loss function.

$$L_{\text{gen}}(W_{\text{rec}}, W_{\text{dis}}, W_{\text{inv}}) = L_{\text{dis}}(W_{\text{dis}}) + \alpha L_{\text{rec}}(W_{\text{rec}}) + \beta L_{\text{inv}}(W_{\text{inv}}) \quad (3)$$

3.2 Discriminative Model

To ensure that the embedded features learned by the generative model have inter-modal invariance, this chapter introduces a modal discriminator D_c and adds two new modal discriminators D_I and D_T on this basis to explore the deep-level inter-modal invariance. During the training phase, h^I is regarded as a positive sample and h^T as a negative sample. They are used as the input of D_c , and their modal categories are classified by D_c . The adversarial loss function $L_{\text{advl}}(W_{D_c})$ is defined on D_c . The core of adjusting W is to guide the direction of parameter updates through gradients and gradually minimize losses using optimization algorithms.

$$L_{\text{advl}}(W_{D_c}) = \frac{1}{n_{\text{train}}} \sum_p \log D_c(h_p^I, W_{D_c}) \quad (4)$$

In the data reconstruction section, this model achieves data reconstruction through two generative adversarial networks respectively, and draws on the idea of cross-modal corresponding autoencoders, that is, using the shared features learned from text data to reconstruct image data and the shared features learned from image data to reconstruct text data. Take image data as an example, its generator is an encoding and decoding network that obtains image reconstruction features i from text data encoding and decoding. On this basis, a discriminator D_i is designed. When the discriminator makes a judgment, it takes the original data features O_i as data and the reconstructed data features i as false data. The discriminator continuously improves its own discriminative ability to determine R as false. In order to produce data that can deceive the discriminator, the generator has to constantly improve its generation ability so that D_i will determine i as true. In this way, the generator and the discriminator train against each other, and eventually the construct feature i is infinitely close to the original data feature O_i , thereby ensuring that the shared features can contain as much semantic information as possible. Its specific loss function is as follows:

$$L_{D_i} = \frac{1}{N} \sum_{p=1}^N \left[\log D_i(O_i^p, \theta_{D_i}) \right] \quad (5)$$

$$L_{G_i} = \frac{1}{N} \sum_{p=1}^N \log(1 - D_i(R_i^p, \theta_{D_i})) \quad (6)$$

$$R_i^p = f_r(O_i^p, \theta_{G_i}) \quad (7)$$

3.3 AI Confrontation Mechanism Network Training Mechanism

When it comes to modal classifiers, it is mentioned that they apply the idea of generative adversarial, that is, shared

features attempt to prevent the modal classifier from identifying which modal category they belong to during the learning process, while the modal classifier itself strives to enhance its own discrimination ability to determine which modal the data belongs to.

Taking the modal classifier in the cross-modal feature association model of the generative adversarial mechanism as an example, the role of the gradient inversion layer is specifically illustrated. When the network performs gradient descent in combination with the loss function of the modal classifier, the gradient after the gradient inversion layer is a normal value, while before the gradient inversion layer its value becomes its opposite. In this case, the social media false in the modal classifier will be updated in the direction of reducing the modal classification loss, while the parameters in the network where the shared features are encoded from the original features will be updated in the direction of increasing the modal classification loss. Under this mechanism, the modal classifier will continuously enhance its own discrimination ability to identify the modal categories of shared features. Since the gradient inversion layer does not change the parameter values during the forward propagation process, the shared features aim to learn data that the modal classifier cannot distinguish as belonging to which mode, thereby confusing the modal classifier. This has led to a kind of competitive and confrontational relationship between the two. The specific training mechanism is shown in Tab. 1.

For the shared features after association, they are required to be consistent in modality and discriminative in semantics. Semantic discriminability means that for any input data, the associated feature should be able to distinguish which category of data it belongs to, such as semantic categories like flowers and birds. In the cross-modal feature association model of the generative adversarial mechanism, a classifier is also designed after the association feature layer, and the classification accuracy is a very good indicator reflecting the semantic

discriminability. Therefore, in this paper, the training sets of Wikipedia, NUS-WIDE-10K and Pascal datasets are used to train the network, and then the test sets of the three datasets are tested respectively to obtain the relevant classification accuracy on the test sets. The specific values are shown in Tab. 2. It can be known from the data in the table that the cross-modal feature association model based on the generative adversarial mechanism has good classification performance for text features. However, since it is difficult to classify certain categories of images in these three multimodal datasets, the classification accuracy for image data is not that high. Overall, this model can ensure that the shared features after association have a certain degree of discriminability.

Table 1 Training mechanism of cross-modal feature association model for generative adversarial mechanism

Input data: training sample $\Omega = \{ip, tp\}$, sample label Y
Output: social media false $\theta_m, \theta_{Gi}, \theta_{Gt}, \theta_C, \theta_D$
Initialize: $\theta_m, \theta_{Gi}, \theta_{Gt}, \theta_C, \theta_D$
Learning rate $\mu \leftarrow 0.000$ update parameters until model fitting:
repeat:
Random assignment
1: Update social media falsity using the stochastic gradient descent algorithm
Semantic classifier: $\theta_C = \theta - \mu$
3: Modal classifier: $\theta_m = \theta_m - \mu \nabla \theta_m LM$; $\theta = \theta + \mu \nabla \theta IL$
4: Correlation error: $\theta = \theta - \mu \nabla \theta ILR$;
5: Triplet error: $\theta = \theta - \mu \nabla \theta ILtrip$;
6: Reconstruct the generative adversarial network: Cross-train the generator and discriminator
Update parameter D (fix parameter G):
Update G parameter (fix D parameter)
return: Train the optimized model and share features C_{pi}

Table 2 Semantic Classification Accuracy

	Wikipedia	NUS-WIDE-10K(National University of Singapore Wide Image Dataset-10000)	Pascal
Text	0.8975	0.8681	0.8525
Picture	0.7127	0.7046	0.6916

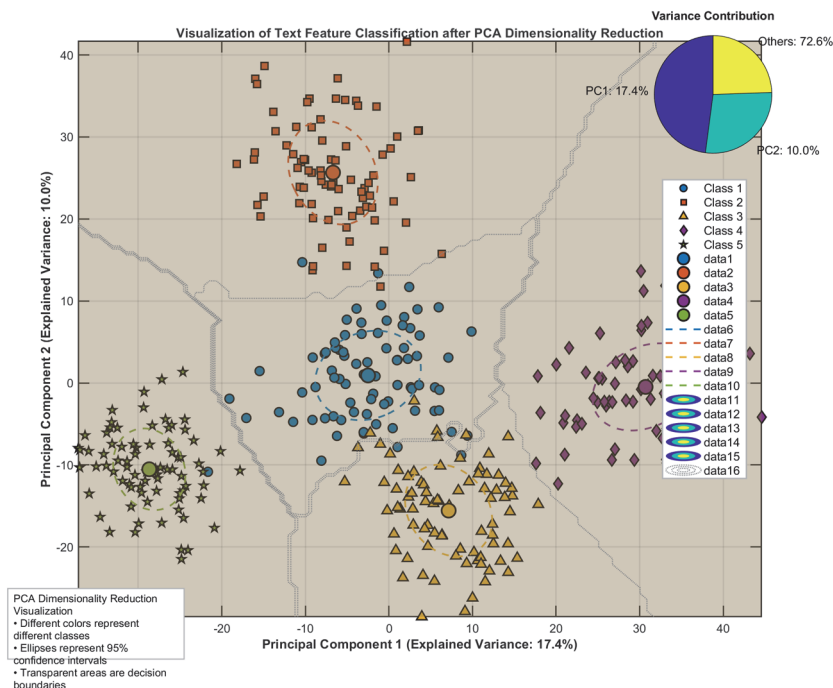


Figure 2 Schematic diagram of classification results after PCA dimensionality reduction (text features)

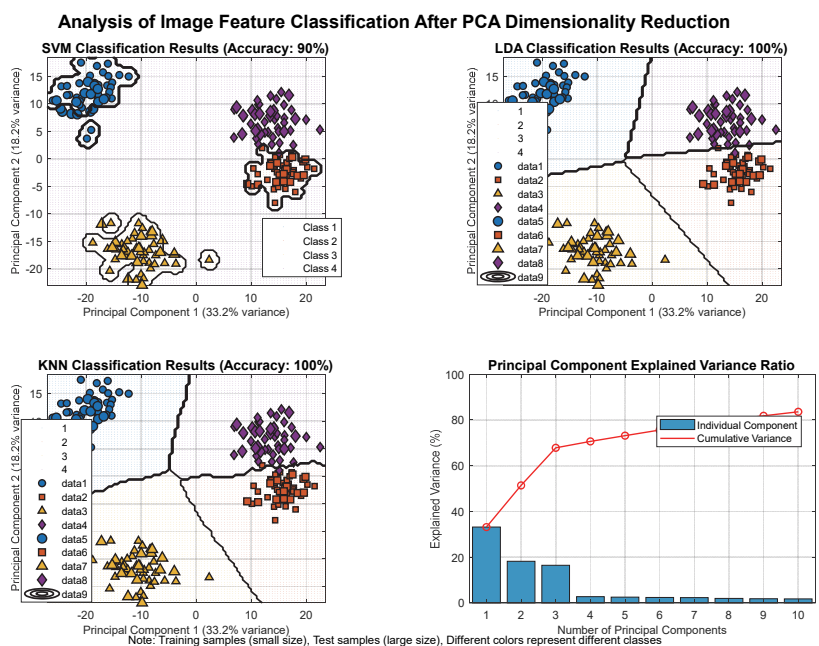


Figure 3 Schematic diagram of classification results after PCA dimensionality reduction (image features)

To verify that the introduction of GRNN networks can improve classification performance to a certain extent, this paper removed the GRNN network and conducted a set of comparative experiments. The corresponding experimental results are shown in Tab. 3. From the data in the table, it can be seen that after removing the GRNN network, the classification performance of the model on the three datasets all decreased. This further indicates that the GRNN network can enhance the classification performance of the model and ensure that the shared features after association are more discriminative of semantics.

Table 3 Semantic classification accuracy after removing the GRNN network

	Wikipedia	NUS-WIDE-10K	Pascal
Text	0.8756	0.8481	0.8125
Picture	0.6927	0.6746	0.6526

To present the above experimental results more vividly, this paper also plots a PCA (Principal Component Analysis) dimensionality reduction scatter plot of the classifier output features for the Wikipedia dataset. The essence of PCA is to perform a linear transformation on the original features while representing them as friendly as possible, and then map them to a low-dimensional space. The specific experimental results are shown in Fig. 2 and Fig. 3. The "Core Distribution Diagram" reveals its key position and functional boundary in the information dissemination network. In short, this schematic diagram macroscopically depicts the concentration and diffusion trend of opinion influence through the contrast between the core and the edge.

4 CONSTRUCTION OF A MODEL FOR INFLUENCING FACTORS OF FALSE INFORMATION VERIFICATION BEHAVIOR OF SOCIAL MEDIA USERS

4.1 Analysis of Influencing Factors of Central Pathways

The central path of information verification behavior refers to the user's in-depth consideration of the content

quality of suspected false information to decide whether to conduct information verification. This study starts from the dimension of information characteristics and systematically examines the key content elements that affect users' behavior of verifying false information. Research has found that core features such as the degree of association between information content and individual users, the authenticity of information presentation, and the popularity level of information dissemination significantly affect users' information verification and decision-making processes. Specifically, suspicious information usually has the uncertain feature of authenticity and the ambiguity of semantics. This characteristic leads users to need to invest a large amount of cognitive resources and time costs to distinguish authenticity. It is worth noting that when the information content is highly relevant to the user's personal interests or forms a hot topic of dissemination on social networks, it will significantly increase the user's level of attention engagement, thereby prompting them to engage in verification behavior. Based on this, this study proposes the following theoretical hypotheses: Under the central path framework of the fine processing possibility model, information relevance (referring to the degree of matching between information and users' personal needs), information simulation degree (reflecting the authenticity level of information forgery), and information topic popularity (representing the intensity of information dissemination in social networks) constitute the three core elements that influence users' verification behavior. These three elements function through dual mediating pathways: on the one hand, they trigger users' emotional fluctuations (such as anxiety, curiosity and other emotional responses), and on the other hand, they activate users' risk assessment mechanisms (rational judgments of potential hazards). Ultimately, they jointly act on users' information verification behavior decisions. This theoretical model not only reveals the influence mechanism of information content characteristics on user behavior, but also provides an operable measurement dimension for subsequent empirical research.

Based on a comprehensive review of the research related to the susceptibility to false information, this section will construct an assessment index system for the susceptibility levels of false information of social media users. An individual's action or the formation of a certain attitude is jointly determined by three aspects: motivation, ability and triggering cues. Among them, motivation stems from an individual's psychological needs, goal orientation, values and other factors, and is the internal force that drives the formation of user behavior or attitude. Ability encompasses an individual's knowledge reserves, cognitive level, thinking structure and skill mastery, etc., and it is the internal condition for users to perform behaviors or form attitudes. Trigger cues are external stimuli, such as information characteristics, presentation methods, and source credibility, which can stimulate or guide an individual's behavior or attitude. The susceptibility of users to false information reflects their susceptible attitude towards it, which is also jointly determined by motivation, ability and triggering cues. Since the construction of the susceptibility assessment index system for false information in this paper mainly takes users as the assessment objects and the cognitive process of users when processing information as the main line, in combination with Fogg's behavior theory, the motivation and ability factors related to individuals will be given priority consideration, rather than the trigger clues related to information. Based on the further analysis of the influencing factors of susceptibility to false information in existing relevant studies, it is found that social media users are not only influenced by motivation-driven and cognitive abilities when processing information [25, 26], but also closely related to their psychological characteristics (such as anxiety, stress, personality traits, etc.) [27]. Therefore, psychological characteristics are incorporated into the evaluation index system.

In conclusion, this paper will construct an assessment index system for susceptibility to false information from three aspects: psychological dimension, ability dimension and motivation dimension. In terms of psychological dimensions, it refers to the degree to which users' emotional states, trust tendencies, risk preferences and other factors guide their interpretation and acceptance of information. This can be summarized as "user psychological characteristics", which is an indicator to measure users' psychological responses when facing false information on the Internet. The ability dimension includes users' cognitive reserves, thinking patterns, information literacy, etc. in specific knowledge fields. These constitute the framework of users' ability to identify false information, which can be summarized as "information cognitive factors". In terms of the motivational dimension, it refers to the intrinsic driving force that users have to identify, share and disseminate information, which is influenced by personal values, social responsibility, etc. It is named "motivational driving factors" and is used as a motivational indicator to measure users' tendency to form a sensitive attitude towards false information.

4.2 Construction of a Model for Evaluating the Susceptibility Level of False Information

Conduct consistency tests on the coordination of

expert scores. When the consistency ratio CR is less than 0.1, it indicates that the consistency of the judgment matrix is good. In this paper, the YAAHP software is used to calculate the consistency ratio of each judgment matrix, as shown in Tab. 4. The consistency ratios are all less than 0.1. It is worth noting that 2×2 judgment matrices (second-order matrices) themselves have consistency and do not require consistency judgment, including A_1-B_1 , A_2-B_2 , A_3-B_3 , B_3-C_1 , B_5-C_1 and B_6-C_1 judgment matrices.

Table 4 Consistency inspection

Indicators at each level	r	$C.I$	$C.R$	$R.I$	Inspection results
$S-A_i$	3.2	0.02	0.01	0.53	Through
B_1-C_i	5.1	0.03	0.02	1.13	Through
B_2-C_i	5.3	0.02	0.021	1.12	Through
B_4-C_i	3.1	0.01	0.03	0.52	Through

As can be seen from Tab. 5, the weight value distribution of the susceptibility assessment index for false information of social media users has the following characteristics:

Among the three first-level indicators, the weight values are not significantly different. Among them, the information cognition factor (0.363) has a relatively high weight, followed by the motivation-driven factor (0.330), and the user psychological characteristics (0.307) have the lowest weight. This indicates that the cognitive methods of social media users towards information analysis, processing, etc. are the most core factors influencing their susceptibility to false information, while motivational driving factors and user psychological factors are important supplements. Among the six secondary indicators, the weights of information literacy (0.263) and psychological factors (0.213) are significantly higher than those of other indicators, while the weight values of personality traits (0.094) and thinking patterns (0.100) are the lowest. This indicates that the information literacy of social media users and psychological factors based on worry, threat, etc. have the greatest impact on the susceptibility to false information. However, the influence of personality traits and ways of thinking is relatively small. Among the 19 third-level indicators, individual benefit (0.145) and health literacy (0.138) have the highest weights, while conscientiousness (0.011), extraversion (0.017) and satisfiability (0.018) have the lowest weights. This indicates that the susceptibility of social media users to false information is more likely to be influenced by their potential personal interests and healthy cognitive levels, while personality traits such as conscientiousness and extraversion have relatively less impact on users' susceptibility to false information. In conclusion, the indicator division path of "information cognition style - information literacy - health literacy" and the individual benefit indicator in behavioral motivation are the key indicator elements influencing users' susceptibility to false information.

In terms of information cognition, among the secondary indicators, the weight of "information literacy" (0.263) is much greater than that of "way of thinking" (0.100), indicating that the literacy of social media users in obtaining, evaluating and utilizing information has a much greater impact on their susceptibility to false information than their way of thinking. Among the third-level

indicators, health literacy (0.138) has the highest weight and is a key element in information cognition. The weight values of the other third-level indicators range from 0.041 to 0.063, with relatively small differences, and they are secondary factors. In terms of thinking patterns, the weight

of analytical thinking indicators (0.060) is slightly greater than that of intuitive thinking (0.041), indicating that the influence of different thinking patterns on users' susceptibility to false information does not mean very much.

Table 5 Weights of evaluation indicators for users' susceptibility to false information

First-level indicator	Secondary indicators			Third-level indicators		
	Indicator	Intra-group weight	Overall weight	Indicator	Intra-group weight	Overall weight
User psychological characteristics (0.307)	Psychological factors	0.695	0.213	Worry mentality	0.171	0.036
				Threat perception	0.248	0.053
				Perception of severity	0.346	0.074
				Satisfiability	0.086	0.018
				Trustworthiness	0.149	0.032
	Personality traits	0.305	0.094	Openness	0.246	0.023
				Agreeableness	0.231	0.022
				Extraversion	0.185	0.017
				Conscientiousness	0.119	0.011
				Emotional stability	0.219	0.020
Information cognitive factors (0.363)	Way of thinking	0.276	0.1	Analytical thinking	0.596	0.06
	Information literacy	0.724	0.263	Intuitive thinking	0.404	0.041
				Information processing capability	0.238	0.063
				Health literacy	0.525	0.138
				Media literacy	0.237	0.063
Motivation-driven factors (0.33)	Cognitive motivation	0.462	0.152	Maintain belief	0.452	0.069
	Behavioral motivation	0.538	0.178	Self-efficacy	0.548	0.083
				Individual benefit	0.819	0.145
				Altruism	0.181	0.032

In terms of motivation and drive, among the secondary indicators, the weights of "cognitive motivation" (0.152) and "behavioral motivation" (0.178) are similar, indicating that the influence of the two different aspects of motivation on susceptibility to false information is relatively small and both are at a medium level. Among the third-level indicators, the weight value of individual benefit (0.145) is the highest, significantly higher than the other three indicators, and it is the core and key element in the motivation dimension. The weight values of belief retention (0.069) and self-efficacy (0.083) have little difference and are in the middle position. The weight value of altruism (0.032) is the lowest, indicating that its influence on users' susceptibility to false information is relatively weak. In conclusion, the individual benefit index in behavioral motivation has the highest weight, indicating that users' susceptibility to false information is more driven by their own interests in terms of motivation.

In terms of user psychological characteristics, among the secondary indicators, the weight value of "psychological factors" (0.213) is much greater than that of "personality traits" (0.094), which indicates that psychological factors such as emotional responses and attitude tendencies have a much greater impact on users' susceptibility to false information than their personality traits. Among the third-level indicators, severity perception (0.074) and threat perception (0.053) have the highest weight values and are the core driving factors. However, the weight values of satisfiability (0.018), extraversion (0.017), and conscientiousness (0.011) were the lowest, and their influence was relatively weak. Other indicator values range from 0.020 to 0.036, which is in the middle position. In conclusion, psychological factors, especially the perception of severity and threat, are the key core indicators of users' psychological characteristics, while the

influence of personality traits is generally weak.

4.3 Susceptibility Assessment Model for False Information

The fuzzy evaluation method will be adopted to assess the susceptibility level of false information of social media users. Firstly, take the third-level indicators in the previous evaluation index system as the elements of the factor set: $S = \{S_1, S_2, S_3, \dots, S_n\}$ ($n = 19$).

Secondly, based on the specific circumstances of the survey questionnaire, the grade of each assessment indicator is determined by five levels: "strongly agree, agree, average, disagree, strongly disagree", representing extremely high susceptibility, high susceptibility, medium susceptibility, low susceptibility, and very low susceptibility in sequence, that is, $V = \{\text{strongly agree, agree, average, disagree, strongly disagree}\}$.

For each indicator, a grade evaluation is conducted to determine their membership degrees r_{ij} for different grades in the evaluation set V . From this, the evaluation set R_i for the i -th indicator can be derived as $(r_{i1}, r_{i2}, \dots, r_{in})$, thereby obtaining the fuzzy matrix of the assessment results of the susceptibility level of false information of social media users.

For the grade evaluation in this paper, the weight value W of the evaluation index calculated in the previous text is combined with the result of the fuzzy matrix obtained through the single-level fuzzy comprehensive evaluation for calculation, thereby determining the comprehensive evaluation vector S of the susceptibility level of social media users to false information.

$$S = (W_1, W_2, \dots, W_N) \cdot R_i \tag{8}$$

Generally speaking, when different people say the

same piece of false content on social media, the duration is likely to vary, and the interval between them may also be different. During the process of collecting false features on MFCC social media, appropriate preprocessing should be carried out on the original signal. To facilitate data processing and ensure sufficient accuracy, the false data from social media is first converted into 64-bit floating-point numbers, and then pre-weighted processing is carried out to minimize the adverse effects caused by lip radiation as much as possible and compensate for the high-frequency attenuation of the signal.

The Mel filter uses the Mel filter to filter digital signals to reduce the masking effect of the human ear. The signals processed by the Mel filter are more in line with the sound perception characteristics of the human ear.

$$H_m(k) = \frac{k - f(m-1)}{f(m) - f(m-1)} \tag{9}$$

Here, $f(m)$ represents the center frequency, as shown in Fig. 4, where the horizontal axis is the frequency and the vertical axis is the amplitude. The bandwidth widens as m increases.

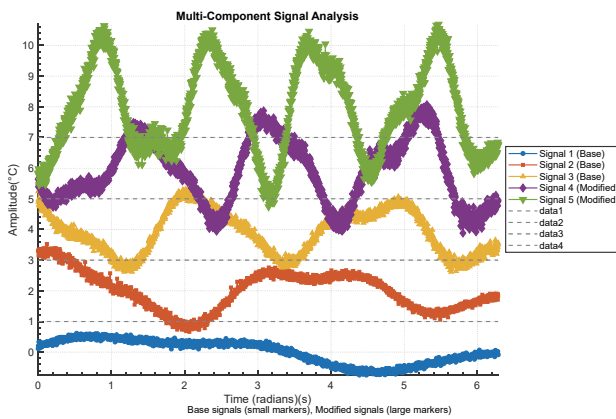


Figure 4 Mel frequency filter bank

5 SIMULATION

This study adopts an empirical research method, taking

active users of social media platforms as the research objects, and collects behavioral data through a standardized questionnaire tool system. In terms of the design of research methods, this study will employ the multivariate statistical analysis technique of Structural Equation Modeling (SEM) to systematically verify the constructed theoretical model. The specific implementation process includes: Firstly, a measurement scale is designed based on the theoretical framework, and user behavior data is obtained through large-scale questionnaire surveys. Subsequently, professional statistical software such as AMOS or Mplus is used to estimate the model parameters using the maximum likelihood estimation method. Finally, through statistical methods such as goodness-of-fit test and path coefficient analysis, the explanatory power and predictive validity of the model are comprehensively evaluated. The research focuses on revealing the multi-dimensional factors and their action paths that influence social media users' participation in the dissemination of false information, including the interaction at various levels such as individual psychological factors, social influence mechanisms, and information characteristic dimensions. Based on the empirical analysis results, this study will construct an integrated "Model of Influencing Factors of Social Media Users' herd Behavior of False Information Dissemination". This model can not only explain the psychological mechanism of users' participation in the dissemination of false information, but also predict the behavioral tendencies of users in different situations, providing a theoretical basis for platform governance. During the model validation stage, the reliability and validity of the research conclusions will be ensured through methods such as discriminant validity tests, aggregated validity tests, and Bootstrapping. As can be seen from Tab. 6, the square root values of the AVE values of all latent variables are greater than the absolute values of the corresponding correlation coefficients, indicating that the discriminant validity among the latent variables is good. In terms of applicability testing, in this study, the KMO value was 0.803, and the significance probability of the X_2 statistical value of the Bartlett sphericity test was 0.000, meeting the significance level requirements and being suitable for factor analysis.

Table 6 Correlation coefficient and square root of AVE

	Information popularity	User engagement degree	Group cohesion	Relevant knowledge and experience	Ambiguity of context	Ambiguity of context	Group consistency	Act of spreading false information in a herd
Information popularity	0.892							
User engagement degree	0.312	0.845						
Group cohesion	0.028	0.434	0.737					
Relevant knowledge and experience	0.117	0.713	0.168	0.902				
Ambiguity of context	0.298	0.078	0.008	0.031	0.871			
Individual reputation	0.146	0.875	0.217	0.558	0.036	0.893		
Group consistency	0.018	0.267	0.492	0.103	0.003	0.123	0.838	
The act of spreading false information in a herd	-0.003	0.451	0.603	0.212	-0.133	0.504	0.513	0.894

Among the 220 online opinion leaders, the information dissemination breadth of -147, 187, 117, 114 and 21 is relatively high, playing a good guiding role in the dissemination of false information knowledge on social media. In terms of recognition, some individuals stand out

-117, 173, 169, 187, 129. They have a high influence on the spread of false information on social media, and at the same time, the public has a high acceptance of the information they spread. In addition, on the whole (as shown in Fig. 5), individuals -147, 117, 187, 173, 169, 35

have relatively high information dissemination capabilities and have a high influence in the community. Their remarks in the Q&A community will directly affect the general users in the Q&A community and play a strong role in controlling the spread of rumors.

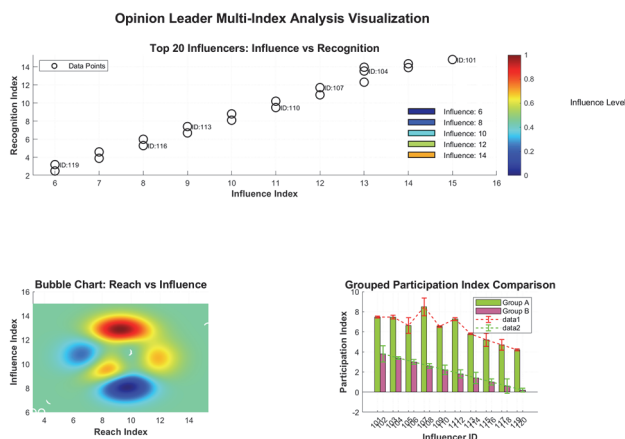


Figure 5 Information dissemination capacity of online opinion leaders

The information dissemination capacity of the entire network can be effectively measured based on information dissemination efficiency, dissemination path and dissemination control degree. The efficiency of information dissemination can effectively assess the flow of information throughout the entire network, mainly measured by density, shortcut distance and network cohesion. The analysis of the information dissemination path in the network mainly involves assessing the depth of an individual's influence in the network to maintain the order of information dissemination in the community. This is mainly measured by the centrality of the network. The degree of control a user has over information refers to the probability that information is disseminated from this user to other users. During the process of information dissemination, the more information a user acquires in the network, the higher the degree of control the user has over the information in the network, and the greater their influence on other users. Conversely, the degree of trust other users have in this user is also higher. In the text, it is mainly measured through structural holes and core-edge structures.

Based on whether there was information interaction among online opinion leaders, an adjacency matrix for information exchange among online opinion leaders was constructed. And the visualization of the network is presented through Gephi software, and the calculation part of measuring network indicators is carried out by using Ucinet software. Based on the information interaction among online opinion leaders, an overall network diagram of online opinion leaders was constructed, as shown in Fig. 6.

In Fig. 6, the circular boxes represent the 220 online opinion leaders on this topic. Individuals of the same color in the figure have similar information interaction frequencies. Meanwhile, the size of the shapes in the figure represents the degree of centrality of each individual. The lines in the figure indicate the relationship ties through which online opinion leaders seek advice or exchange information. It can be clearly seen in Fig. 3 to Fig. 6 that there are no isolated nodes in the information

dissemination network of opinion leaders in the entire knowledge Q&A community network, indicating that the 220 online opinion leaders in this topic community have no information silos and all information can reach them.

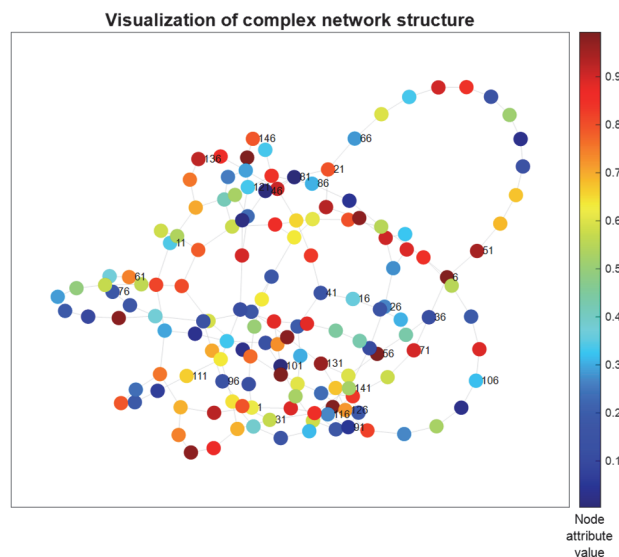


Figure 6 Overall network analysis chart of online opinion leaders

After the overall network graph is constructed, it is necessary to evaluate the network's propagation efficiency through relevant indicators. The main indicators employed include: overall network density, shortcut distance and network cohesion. The overall density of this network is 0.0414, which is much less than 1. The relatively low overall density also indicates that the overall connection among opinion leaders in the information dissemination network is rather loose. Since the calculated shortcut distance of the entire network is 2.922, it means that each individual has to pass through an average of three people in this network before communicating with other individuals, resulting in relatively low network dissemination efficiency. In addition, the cohesion of the network is 0.246, which indicates that the overall network is relatively loose, and the closeness between individuals and the dissemination efficiency need to be improved.

The propagation control degree of a network is measured by the number of structural holes existing in the network. The central potential data of the network indicates that there are some nodes located at the structural hole position in the network. Individuals at such nodes can also connect to two regions of the network, obtain non-redundant information in the network, and have a relatively high right to obtain information. Meanwhile, through the calculation results, it is found that there is an obvious core-edge structure in the information dissemination network. Combining the structural hole attribute of network opinion leaders and the analysis of the core-edge structure, Fig. 7 is drawn.

Through the analysis in Fig. 7, it is found that there are 52 network opinion leaders in the core area of the entire information dissemination network, and the individuals in red and boxes indicate that they are located in the structural holes of the network. On the one hand, by combining the core-edge structure with the information dissemination ability of network opinion leaders analyzed in 3.3.2, among the top 30 network opinion leaders in the information

dissemination ability table, 26 are in the core area, accounting for 86.67%. Therefore, users with higher personal communication capabilities are more likely to be in core positions, and their information exchange behaviors will have a higher impact on other individuals in the community. On the other hand, by analyzing the two indicators of structural holes and core-edge structures, it is found that, except for individuals -166 and 217, the other individuals located at the structural hole positions are also in the core area of the network at the same time. These individuals have an excellent positional advantage. They have greater access to information and thus are more competitive than members in other positions within the network.

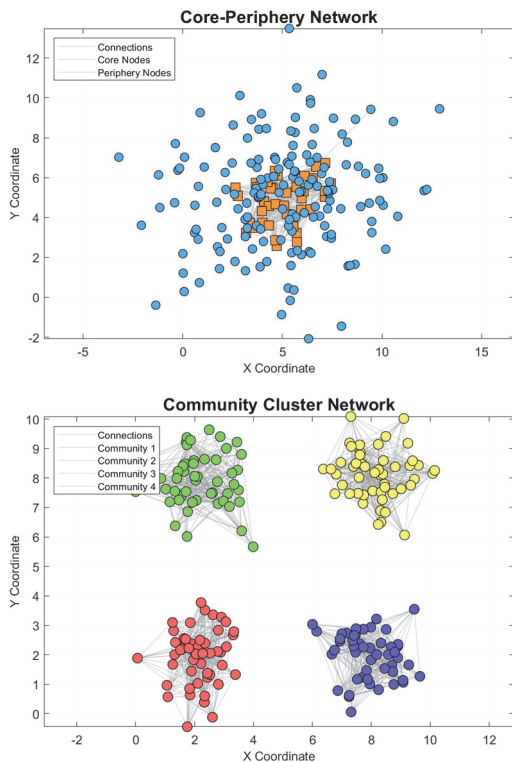


Figure 7 Schematic diagram of the distribution of core and edge areas of network opinion leaders

Fig. 8 shows the trend of the proportion of daily emotional tendencies of popular topics that are falsely related to social media. Through a seven-month continuous sentiment analysis, we can find that users' emotional tendencies throughout the data collection period are mainly divided into three stages.

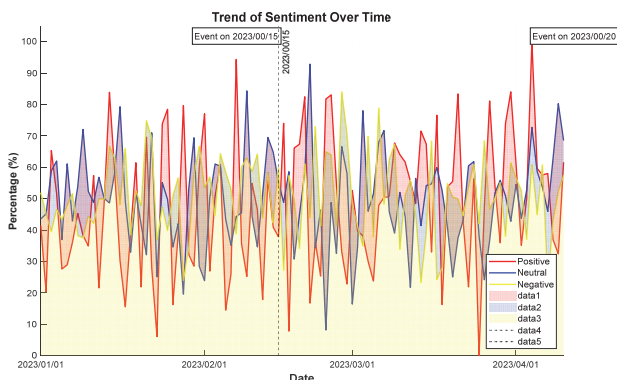


Figure 8 Daily comment sentiment proportion

The model is used for word-level prediction of social media falsity, and the prediction results are input into the word-level special of the hierarchical prosodic model for training. The target adversarial samples are generated by minimizing the loss function. The generated adversarial sample waveform diagram is shown in Fig. 9.

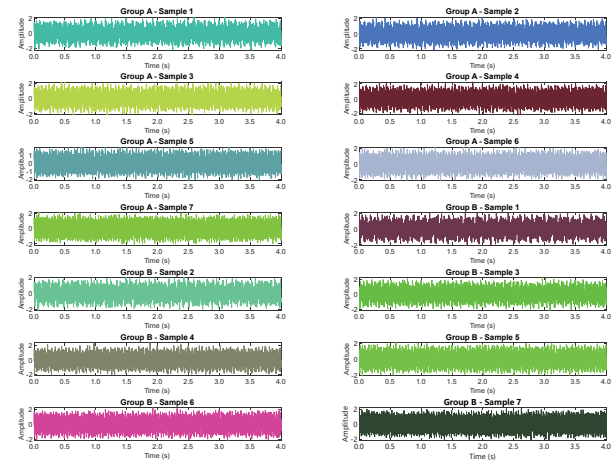


Figure 9 Adversarial sample waveform of the sample

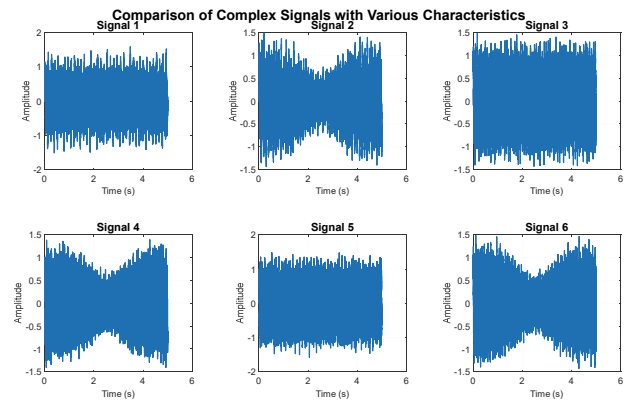


Figure 10 Samples of false confrontation on social media

As shown in Fig. 10, the anti-social media false waveform graph generated by the social media false prosodic feature extraction method proposed in this paper is closer to the original social media false, has less disturbance, is less detectable by the human ear, and has a higher similarity to the target social media false, resulting in a better attack effect.

6 CONCLUSION

This study proposes an innovative cross-modal feature association learning framework, which achieves semantic consistency representation of multimodal data by deeply integrating generative adversarial networks and feature alignment mechanisms. The core innovation of this algorithm lies in the following: Firstly, a dual-branch modal discrimination network is designed, and a deep neural network architecture is utilized to accurately classify text and visual modal data; Secondly, a Gradient Reversal Layer is introduced to construct an adversarial learning mechanism, enabling the feature extraction network to be optimized in the opposite direction of the parameter update of the modal classifier. This unique

adversarial training strategy prompts the generated feature representation to have the following characteristics: (1) Modal invariance: Through the dynamic game between the modal classifier and the feature extraction network, modal-specific features are effectively eliminated; (2) Semantic discriminability: Semantic classifiers combined with supervised learning ensure that the shared feature space maintains clear category boundaries. Experiments show that this algorithm significantly improves the robustness and discriminative ability of feature representation in cross-modal retrieval tasks. In the research on the dissemination behavior of false information, this study, through large-scale empirical analysis, identified four key influencing factors: group cohesion (reflecting the connection strength among group members), group consistency (representing the degree of uniformity of group opinions), individual reputation (reflecting the credibility of users in social networks), and situational ambiguity (describing the degree of certainty of the information environment). The research results show that: 1) Group cohesion has the strongest positive predictive effect on conformity communication behavior, indicating that close group relationships will significantly increase users' tendency to conformity communication; 2) Group factors influence user behavior through dual paths: they not only have a direct effect on herd communication but also produce an indirect effect by enhancing group consistency (the indirect effect accounts for 35% of the total effect). 3) The influence of the group environment far exceeds that of individual factors. This finding provides an important theoretical basis for the group intervention strategies of social platforms. Based on these findings, this study constructed a multi-level influence model that encompasses both the group level and the individual level, providing a new analytical framework for understanding and predicting the behavior of false information dissemination. The next step will be to track down and hold accountable those who spread false information on social media platforms, and increase the severity of penalties. By improving laws and regulations, supervising and punishing the dissemination of false information, and increasing the cost of following the crowd to spread false information. At the same time, measures such as "publicly clarifying and issuing apology statements wherever false information is spread" are adopted to make social media users more cautious and rational when disseminating information.

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