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Media system dependency theory: Emotional expression on Sina Weibo

Chenwei Ma [1] ,Sharifah Sofiah binti Syed Zainudin[1] , Wan Anita Wan Abas[1]

Abstract

In order to guide the correct direction of public opinion on public events and create a harmonious and healthy social atmosphere, this paper uses media system dependency theory to study the current Sina Weibo platform, which has the highest national discussion, for emotional expression. In this paper, RNN recurrent neural networks and their improved algorithms GUR-LSTM and LSIN-LSTM are introduced for Sina Weibo user attention and self-attention mechanism and Sina Weibo user input layer construction. The algorithm model is then validated to ensure its validity, followed by full-text algorithm validation based on information from the database to clarify the formation of the main communication symbols and interaction ritual chains of Sina Weibo emotional expressions and the correlation between Sina Weibo emotional tendencies and emotions. The results show that "pictures" and "audio" are the least frequent communication symbols in the selection and use of Sina Weibo, accounting for 0.1% of the total, while "multiple symbols" is the most frequent symbol, accounting for 76.4% of the total. The top symbol, accounting for 76.4%, is "multiple symbols". At the significance level of 0.1, the asymptote of the emotional score model is 0.218, and the asymptote of the emotional media is 0.572, which means that the regression coefficients of each explanatory variable are significant. Therefore, the research results of this paper have credibility and can be applied to the study of Sina Weibo users' emotions, and then extended to other media field studies.

Keywords: *media system dependency; Sina Weibo; RNN neural network; GUR-LSTM algorithm; LSIN-LSTM algorithm*

Introduction

In recent years, the rise of social media waves such as Sina Weibo and WeChat has become increasingly embedded in all aspects of citizens' lives, and social transformation has brought about the development of crises and the emergence of contradictions, making it increasingly difficult for governments to manage crisis communication (L, 2022). In traditional research, changes in public perceptions, attitudes and behaviors are important indicators of communication effectiveness. However, public sentiment is emerging as a new indicator of government crisis communication, especially in the context of a "highly selective media environment" for political communication, where citizens' access to information is greatly expanded, but the accompanying expression of emotions and emotional catharsis is also increasingly polarized and fragmented (Liu, 2022). The diversity of communication methods

[1] Faculty of Modern Languages and Communication, Universiti Putra Malaysia, Serdang, Selangor, 43400, Malaysia
Corresponding author Chenwei Ma (machenwei199328@163.com)

allows the public to express more diverse emotions, and the "spectator" and "gathering" effects give the public a sense of identity and emotional resonance, which makes emotional guidance in crisis communication gradually rise in importance (Du, Kowalski, Varde, de Melo, & Taylor, 2020).

The Internet dependence survey found that men were more likely to be Internet dependent than women, and that dormitory access to the Internet and ownership of a personal computer were also significantly correlated with Internet dependence. The literature (Ferris & Hollenbaugh, 2018), in a study of facebook, considers dependence as some kind of interrelationship between an individual and the medium. "This dependence can reach a level that affects the user to a deep emotional degree and tends to a state of indulgence". The perception of the degree of dependence differs in the different disciplinary categories of communication and psychology, but whether or not dependence is considered to cause damage to the individual's physiology and psychology, this continuous desire for media use behavior has a profound emotional, cognitive, and psychological impact on the individual. In the literature (Kayiş et al., 2016), studies on the effects of neuroticism personality on media dependence and Internet addiction, domestic and international studies have largely concluded that neuroticism has a significant positive predictive effect on it. The literature (Panger, 2017) pointed out that there is a low to moderate correlation between people's updated emotional states in social media and their real emotional lives, and that emotional statements in social media can be used as a valid basis for inferring people's real emotional life states to some extent. They also found that social media did not push people into a frenzy, but rather it calmed users, and the main features of the emotional experience of browsing social media were slightly biased towards the dissolution of negative emotions. The literature (Hoffner & Lee, 2015) suggests that social support is negatively related to cell phone dependence. It was found that cell phones had a significant effect on the regulation of negative emotions in individuals who received little social support.

A study of Sina Weibo users found that "convenient access to media facilitates the formation of Sina Weibo dependency. Sina Weibo dependency is both a result of active media satisfaction seeking and a significant passive and non-purposeful nature of the audience". By comparing the new media with the traditional media, the different reliance of the audience on news content was explored, and it was found that younger and more educated audiences rely more on the new media. The literature (Choi, Lee, & Ji, 2021) discusses how the emotions conveyed by news visuals and the positivity of news texts are related to three engagement activities of users' shared comments and reactions. They found that while users often reacted to news that conveyed positive emotions, they were less inclined to share and comment on them, and the most prominent emotion overall associated with user engagement activities was sadness. The literature (Andalibi, Haimson, Choudhury, & Forte, 2018) points out that the anonymous communication space provided by social media is an important channel for them to seek support and receive it, and that the design of social media should take full account of the anonymity function as a socially important dimension of value. The literature (Dale et al., 2020) (Buffard & Papasava, 2020) suggests that brands in social media can use emotional content to increase engagement and conversion rates, introducing the concept of "networked emotional news" and combining it with emotion research and news value theory, finding that social media users are emotionally involved in He found that social media users engage with news stories that have positive emotional content in an emotionally engaging way. It is important to study Sina Weibo emotional expressions for social public relations and government opinion emotional guidance under the perspective of media dependence. According to the influence of algorithmic recommendation on media publicness, this paper introduces an artificial neural network, RNN recurrent neural network, and its improvement algorithm in the research process, and the whole paper is divided into three parts. The first part introduces the media-system dependency theory and clarifies the theoretical basis of the research, which then leads to the RNN algorithm and GUR-LSTM algorithm and LSIN-LSTM algorithm, and constructs the Sina Weibo user portrait to lay the technical foundation for the full-text research. The second part validates and analyzes the model algorithms in this paper, constructs Sina Weibo users and word datasets to verify their fit and determines the credible effect of the algorithms. The third part focuses on the emotional expressions on Sina Weibo, exploring their causes, characteristics of emotional tendencies and emotional interactive expressions, and studying the control direction of opinion dissemination.

Media dependence

Media-system dependency theory

Media-system dependency theory was originally proposed by Melvin Devereux and Bauer-Kiloch in 1976, and it examines the relationship between the influence and importance of a medium and dependence on it (Arslan, Yıldırım, & Zangeneh, 2021). The central idea of media-system dependency theory is that audiences rely on the information provided by the media to satisfy their needs and achieve their goals. This idea is in line with the basic ideas of use and satisfaction theory, but it is clear that media-system dependency theory is not just about audience dependence on the media, or about individual micro-level effects and impacts, as is the case in use and satisfaction research (Meese & Hurcombe, 2021). The theory examines the effects of media communication in the context of a larger social system: "The basis of media influence lies in the connection between the larger social system, the role the media plays in this system, and the relationship between the audience and the media." This dependency includes how audiences use the media to acquire, transmit, and exchange social information, to satisfy entertainment, to shift emotions, and to rely on media messages for goal orientation. This "target-resource" based media dependency is a key factor in explaining the social effects of mass communication.

Knowledge of Twitter Sentiment Sequence Modeling

The most frequently used algorithms in the field of media research are deep learning method and artificial intelligence algorithm, and this paper has been validated to determine the choice of artificial neural network and its improvement algorithm for full-text research.

RNN Neural Network

Recurrent neural networks are a common way to model sequences. RNNs introduce memory to retain historical information, and the memory h_t at moment **t** is jointly determined by the memory h_{t-1} at the previous moment and the input x at moment t.The forward propagation memory state h_t is refreshed at each moment **t** and the parameter matrix U,W,V remains unchanged. The parameter matrix U,W,V is updated sequentially during the back propagation. The computation of memory state h_t and output y_t in forward propagation is shown in equations (1) and (2), respectively:

$$h_t = \sigma(Ux_t + Wh_{t-1} + b) \tag{1}$$

Where U,W is the parameter matrix, b is the bias, and σ is the activation function, typically $tanh$.

$$y_t = \sigma(Vh_t + c) \tag{2}$$

where V is the parameter matrix, c is the bias, and σ is the activation function, typically $softmax$.

GUR- LSTM Long and Short Term Memory Unit and Gated Loop Unit

Basic RNN networks have to multiply the gradients continuously in time steps during backpropagation, and in the case when the length of the input sequence is too long, RNNs can lead to gradient disappearance or gradient explosion problems. The long and short-term memory unit solves to some extent the problem that RNNs cannot train longer sequences of data (Di & Wang, 2021) (Rahman & Hasan, 2021).

The gated cyclic unit prediction effect is close to LSTM with fewer training parameters and only two gate structures of reset gate and update gate, which is a simplification of LSTM structure. This paper uses GRU unit for user sequence modeling of long and short term user behavior. The GRU forward propagation process is:

(1) Calculate the update gate and reset gate:

$$z_t = \text{sigmoid}(W_z x_t + U_z h_{t-1} + b_z) \tag{3}$$

$$r_t = \text{sigmoid}(W_r x_t + U_r h_{t-1} + b_r) \tag{4}$$

where z_t is the update gate, which is responsible for controlling the historical state information

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retained by the current state and the new information received from the candidate states. r_t is the reset gate at moment **t**.

(2) Update the candidate status by resetting the gate and the previous moment memory h_t:

$$\tilde{h}_t = \tanh\left(x_t W_{xh} + h_{t-1} W_{hh} + b_h\right) \quad (5)$$

(3) Calculate the current moment memory h_t:

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t \quad (6)$$

Sina Weibo user attention and self-attention mechanism

The attention mechanism makes reference to the feature that the human brain selectively focuses its attention on the primary target when processing an overload of information, and its success in many fields has demonstrated the effectiveness of the attention mechanism (Niu, Zhong, & Yu, 2021). The basic attention mechanism is used in the ranking model of this chapter to assign different weights to the long-term behavioral characteristics and short-term behaviors of users, and the specific steps of the basic attention mechanism operation are shown in Figure 1.

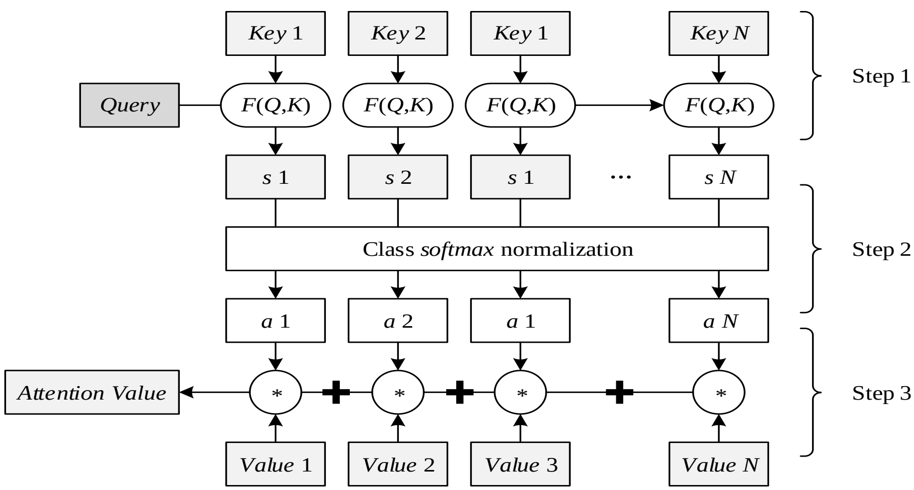

Figure 1: Basic attention mechanism

The calculation process of basic attention can be divided into three steps:

(1) Calculate the similarity between $Query$ and Key_i using dot product, cosine similarity or neural network s_i. The similarity between the two using neural network can be expressed as:

$$Similarly\left(Query, Key_i\right) = MLP\left(Query, Key_i\right) \quad (7)$$

(2) The obtained similarity s_i is normalized to obtain the weight a_i, which can be obtained using the $softmax$ function:

$$a_i = softmax\left(s_i\right) = \frac{e^{s_i}}{\sum_{i=1}^{N} e^{s_i}} \quad (8)$$

(3) The corresponding $Value_i$ and a_i are weighted and summed to obtain the final attention value:

$$Attention(Query, Key, Value) = \sum_{i=1}^{N} a_i \cdot Value_i \quad (9)$$

The self-attentive mechanism considers the correlation between different parts of the input and is calculated as follows:

(1) For each input vector multiply by different matrices to obtain $Query, Key$ and $Value$ respectively:

$$Q = W_q \cdot I; K = W_k \cdot I; V = W_v \cdot I \quad (10)$$

where Q, K, V denotes $Query, Key$ and Value, respectively, and I denotes the input vector.

(2) Calculate the correlation using the obtained Q, K. In order to prevent the inner product from being too large, it is often divided by the scaling factor $\sqrt{d_k}$, and then the weights are obtained by $softmax$ and then weighted and summed with $Value$:

$$Attention(Q, K, V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (11)$$

The self-attentive mechanism does not consider the location information between input sequences, and location encoding needs to be introduced when performing sequence modeling. This chapter focuses on extracting user long-term behavioral features using the self-attentive mechanism.

LSIN-LSTM User Long-Term Interest Network

In this chapter, a ranking model combining users' long-term and short-term behaviors is

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proposed to predict users' click rate on candidate item v_t. The model network structure is shown in Figure 2.

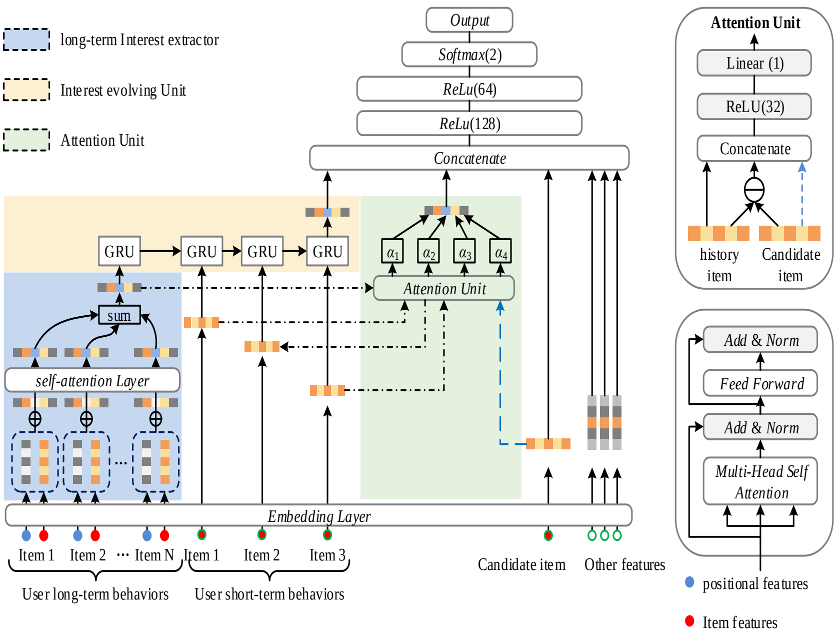

Figure 2: Network structure of LSIN model

For user **u**, its behavioral sequence characteristics can be expressed as:

$$S(u) = \{v_1, v_2, v_3, \ldots, v_n\} \quad (12)$$

$L(u) = v_1 \cup v_2 \cup v_3 \cup \ldots \cup v_{n-k}$ is chosen as the long-term behavior of user u, and the recent k behaviors $v_{n-k+1}, v_{n-k+2}, \ldots, v_n$ as the short-term behavior of user u. The model input consists of user's long-term behavior, user's short-term behavior, candidate items and other features, and the output is the CTR click probability of the user for that candidate item. The model function can be expressed as:

$$CTR = F\left(L(u), v_{n-k+1}, \ldots, v_n, candidate\ item, other\ features\right) \quad (13)$$

The LSIN model consists of input layer, embedding layer, long-term interest extraction layer, interest evolution network, attention unit, and MLP layer, etc. The characteristics of this model are as follows:

(1) The behavioral data of users are divided into long-term and short-term behaviors for modeling separately. The long-term behaviors of users are feature extracted using the self-attention mechanism as the stable preferences of users. Short-term behaviors are directly input into the model.

(2) Sequential modeling of multiple short-term behaviors of users and long-term behavioral features extracted through self-attention by GRU units, as well as assigning different attention weights to user behaviors through the basic attention mechanism, respectively, enable the model to synthesize sequential modeling scenarios and scenarios in which different weights of user behaviors are assigned to directly dominate the current interests of users.

Sina Weibo user input layer construction

All available features in the input layer are shown in Table 1. All input features are divided into three categories to be input into the model: user long-term behavior, user short-term behavior and other features.

Table 1 Available Features

category	features	type
item features	item_id	one-hot
	genres	multi-hot
	avg_rating	numerical
user features	user_id	one-hot
	gender	one-hot
	Avg_rating	numerical
	rated_items_ids	multi-hot
user behaviors features	Item_id	one-hot
	rating	numerical
context Features	rating time	numerical

Both long- and short-term user behaviors can be obtained from the user's historical behaviors. If the sequence of user behaviors in time order is n, the last k items are taken as user short-term behaviors and the rest are taken as user long-term behaviors. For the long-term user behavior features, it is also necessary to send the location encoding to the Transformer network together with them to facilitate the subsequent feature extraction, so the long-term behavior is represented as follows:

$$v^L = \left(v_{item}, v_{pos}\right) \quad (14)$$

$$L(u) = \left\{v_1^L, v_2^L, v_3^L, \ldots, v_{n-k}^L\right\} \quad (15)$$

User short-term behavior $S(u) = \left\{v_{n-k+1}^S, v_{n-k+2}^S, \ldots, v_n^S\right\}$ is directly input to the network without location coding, where $v^s = v_{item}$. user features from Table 1, scene features and other features are all input to the network as other features.

Model algorithm validation and analysis

The LSIN model is evaluated offline to validate the performance of the LSIN model by testing it against other models with different evaluation metrics on different datasets.

Weibo dataset

Two public datasets were used to verify the effect of the LSIN model, and the statistical results of the Sina Weibo dataset are shown in Table 2. Netflix was the official dataset in the contest, and due to the original data being too large, the voting data of 40,156 users on 8640 Sina Weibo events were extracted as the measurement data in this paper.

Table 2 Statistics of Sina Weibo Datasets

dataset	users	items	interactions	sparsity	rating
weibo -1m	7120	4926	1,000,321	95.60%	[1-6]
weibo -10m	7964	10754	10,000,120	98.70%	[0.5-6]
Netflix	40165	8640	11,824,670	99.40%	[0-6]

Feedback of the algorithm model in offline conditions

Impact of different ways of modeling under offline conditions

The effect of modeling approach on offline AUC is shown in Table 3. The effect of long-term and short-term behavior division on predicting candidate items was compared by varying the ratio of long- to short-term behavior: in addition to comparing which of the two modeling approaches, basic attention and GUR module, contributed more to the final results.

Table 3 Impact of modeling methods on offline AUC

dataset	method	AUC	dataset	method	AUC
weibo -10m	LSIN-A	0.791	Netflix	LSIN-A	0.7740
	LSIN-B	0.7560		LSIN-B	0.7468
	LSIN-C	0.8476		LSIN-C	0.8436

Effect of model hyperparameters

The impact of the dimensionality of the embedding vector on the offline AUC is evaluated, and the impact of Embedding sizes on the offline AUC is shown in Figure 3. The overall performance of the model is best when the embedding dimensions are in the range of 50-80. Too low dimension of embedding vector will lead to insufficient representation of user behavior

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characteristics, while the enhancement effect is not obvious when the dimension is too high, and the model parameters are greatly increased leading to easy overfitting of the model. The algorithm in this paper is effective for network ranking and is applicable to the study of Sina Weibo data and topic traffic.

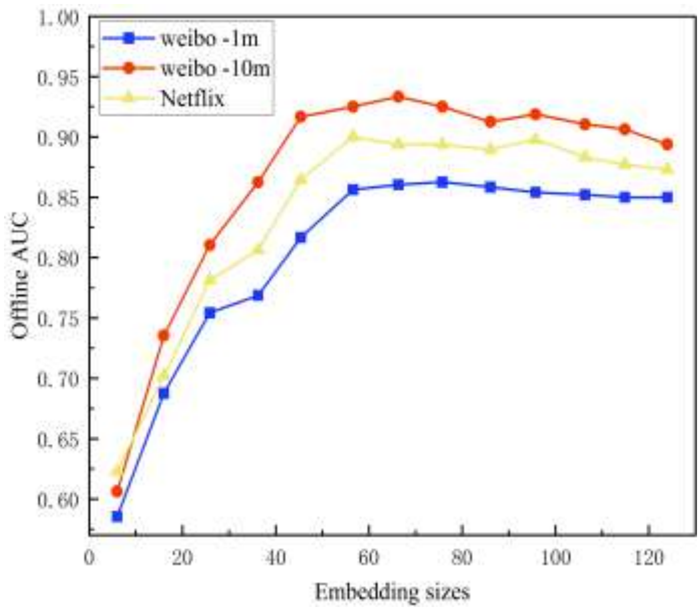

Figure 3: Impact of Embedding sizes on offline AUC

Sina Weibo emotional expression

The communication symbols on Sina Weibo

Communication activities have gone through several stages, such as oral, written, printed, electronic, online, and mobile Internet. According to Neil Bozeman's view of "media as metaphor", technology is never neutral, and any communication technology, tool, or medium has its own characteristics, which will also produce bias in the communication process, including the bias in the use of communication symbols and the resulting bias in the content of communication, ultimately leading to bias in people's In other words, different communication symbols will give people a better impression of their sensory experience. In other words, different communication symbols will have different effects on people's contact habits, contact evaluation and contact effects, which will lead to differences in people's attitudes and behaviors in understanding the world and the world.

In order to measure the expression of emotion on Sina Weibo in a more standardized way, communication symbols were included in the scope of investigation. By reading the literature and collecting the corpus, we used "which symbols are used to express emotions" as the variable and set "text", "picture", "video", "emoji" and "multiple symbols" as the variables. "audio", "video", "emoji" and "multiple symbols" were used as variables to quantify the symbols of Sina Weibo. The frequency statistics of Sina Weibo communication symbols are shown in Table 4.

Table 4 Statistics of Weibo Communication Symbol Frequency

Propagation symbol type	Propagation frequency (times)
written words	720
picture	10
audio frequency	15
video	621
emoticon	650
Composite propagation of multiple symbols	1864

The study found that in terms of the choice and use of communication symbols, "pictures" and "audio" were the least frequently used on Weibo, with only 10 and 15 times, accounting for 0.1% of the total number of times. "Emoticons" were used 650 times, accounting for 1.1%. The frequency of "text" took the second place, reaching 720 times, accounting for 22.3%. The first communication symbol, accounting for 76.4% of the total, was "multiple symbols", which appeared 1,864 times. In the current era of integrated media communication, communication symbols are more diversified and users have more choices, so there is no doubt that "multi-symbol composite communication" accounts for a significant proportion, but it is undoubtedly surprising that the older text symbols can account for such a large proportion.

The ritual chain of emotional communication interaction on Sina Weibo

The interactive ritual chain theory proposed by Collins is a theory of context, where interactive rituals are a set of processes with causal associations and feedback loops. The following four elements are required for them to occur: First, two or more people are gathered in the same place. Second, the place sets boundaries for outsiders. Third, people focus their attention on a common object or activity. Fourth, people share a common emotional or affective experience with each other. When feedback is formed between these elements and they are effectively integrated, accumulating to a high degree of mutual attention and emotional sharing, interactive participants experience the following:

a. Group solidarity.

b. The emotional energy of the individual.

c. Symbols or "sacred objects" that represent the group.

d. The moral sense of maintaining the group and respecting its symbols.

The core of the interactive ritual is a process that evolves over time, in which participants interact to create a common focus of attention, sensing each other's bodily micro-rhythms and emotions, and forming a better model of mutual attention and emotional connection.

Sina Weibo emotional tendencies and the formation of emotions

The expression of emotions on Sina Weibo

In his discussion of the affective connectivity model of the interactive ritual chain, Collins emphasizes that joint attention is the key to developing shared symbols. He argues that rhythmic cooperation and emotional connection are essential components of interactive rituals, and that a focus of mutual attention is essential. Collins' focus can refer, in part, to both the issue focus of the participating members and the emotional focus between them.

In this study, the weibo-10m database was used to determine the frequency of the use of Weibo symbols, and the "text" symbol was selected as the research feature.

For the discussion of the new crown epidemic in 2020, the largest percentage of people with a neutral attitude on Weibo is 62%, followed by a very positive percentage of 19.8% of Weibo postings, and overall it seems that most netizens have a rational attitude regarding the epidemic prevention and control measures in 2020. As for the communication of very negative and negative emotions, the percentage of negative emotions is very high 11.9%, even higher than the total percentage of positive blog posts 9.8%, which shows that in the case of more significant public health events, netizens mostly have a fear psychology, which in turn leads to emotional attitude anxiety and even behaviors such as verbal attacks on others.

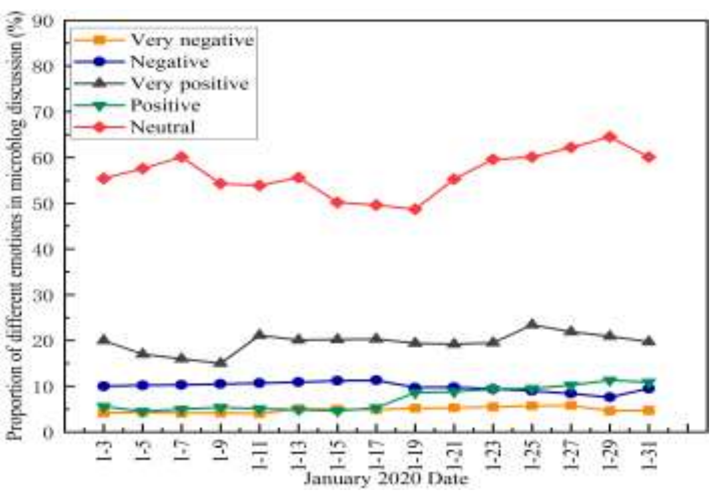

Figure 4: Emotional Feedback on Weibo of COVID-19 in January 2020

Communication effectiveness of emotional attitudes on Sina Weibo

Based on the research in the previous subsection, the sample data of events in the Sina Weibo dataset were calculated based on the sample information of the Sina Weibo dataset using the

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LSIN-LSTM user long and short-term network model, and the median and plural of the sentiment scores were introduced in the process to do the Kruskal-Wallis test, and the median and K-W result tests of the sentiment scores on Sina Weibo are shown in Table 5, and the results of the Mann-Whitney test on Sina Weibo are shown in Table 6.

The regression coefficients of each explanatory variable are significant. the Mann-Whitney significance is 0.418 and 0.642 respectively, and the auxiliary verification introduced also holds.

Among the five sentiment indicators selected in this paper, the two indicators of "neutral" and "very positive" have the most significant impact on public sentiment.

According to communication theory and the coefficients of each explanatory variable, the higher the degree of "individualism", the more positive the expression of emotion. The stronger the "masculinity", i.e., the preference for competition, achievement, power, ambition and materialism, the more negative the expression of emotions.

The higher the degree of "risk aversion", the stronger the sense of crisis and motivation, the lower the sense of happiness, and the more negative the emotions.

The negative coefficient of "global freedom" indicates that when a country has more freedom of expression in the media platform, more negative emotions will emerge, in other words, public expression will be restricted to a certain extent, which will cover up some of the negative emotions. "The negative coefficient of the Human Development Index indicates that the higher the level of economic development, the more negative emotions the public has and the less likely they are to be satisfied and happy, but this negative effect is relatively small.

This proves that the most direct impact on the effectiveness of emotional communication in Weibo is the amplified overly negative or overly positive emotions, while the "neutral" people make up the majority of each Weibo news, but their wait-and-see attitude does not directly cause emotional conflicts to Weibo users.

Table 5 Median emotional scores on Sina Weibo and K-W results test

	Sentiment-mode	**Sentiment-median**
Chi square	5.704	2.741
df	5	5
Progressive significance	0.218	0.572

Table 6 Weibo Mann Whitney Test Results

	Sentiment-mode	**Sentiment-median**
statistical test	504.600	607.600
Wilcoxon W	1802.600	1829.600
Z	-2.547	-1.807
Progressive significance	0.418	0.642

Emotional Expression on Sina Weibo in the Perspective of Media Dependency

Emotional expression of event outbreak on Sina Weibo

In sudden public events, government departments should take active measures for crisis communication and emotional guidance, so that the public can respond to the ensuing crisis in a good frame of mind and have a good influence on the public's emotional perception as well as the development direction of the crisis. During the outbreak period, the emotional feedback on Sina Weibo presents different changes according to different levels of crisis communication, while the government mainly gives information back to the public by providing guiding and debugging information, and the emotional expression of netizens at the early stage of the event outbreak is shown in Figure 5.

Under the actual operation of the GUR-LSTM algorithm, negative negative emotions outnumbered positive positive emotions under both strategies of providing guidance messages and debugging messages. Under the government-led guidance message, the number of supportive voices increased significantly, reaching 40%; sadness was the second highest at 28%, anger at 16%, and anxiety at only 1%, which indicates that the government-led guidance message has a certain effect on alleviating public emotions. After the adoption of the debugging strategy, the majority of the sample's emotions changed to "sadness", which is mainly a change in the emotions of the truthful netizens in response to the incident itself.

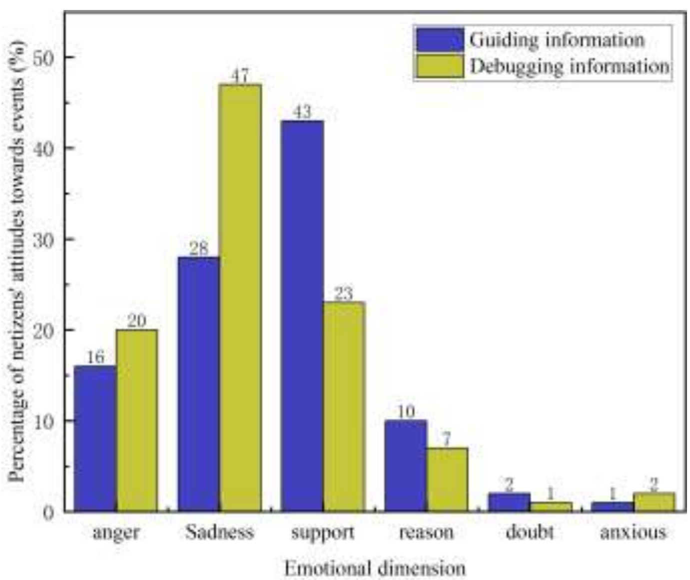

Figure 5: Emotional expression of netizens at the beginning of the incident

Expressive features of Sina Weibo emotional interaction

This paper argues that the emotional interaction chain formed in Sina Weibo emotional communication has the following two results: the maintenance of "engagement" and the generation of "emotional memory".

(1) Sense of participation: the maintenance of group rituals

A sifting through the words in the Weibo dataset reveals that whether it is the questioning of authority by participants in the topic "New crown epidemic prevention and control" to realize the "true cause" or the "I love you China" topic in which members hold up the "patriotic master" banner, such group solidarity is facilitated by the movement around the movement ceremony. Or the "I love you China" topic in which members raised the banner of "patriotism," the movement of netizens around the moving ceremony contributed to the achievement of group solidarity, a symptom of which is "participation. Collins believes that a successful interactive ritual will produce four types of results, namely group solidarity, individual emotional energy, group symbols and moral sense, and all four types of interactive ritual results are closely related to netizens' "sense of participation".

As an emerging concept, "engagement" first emerged in the field of economics and has received widespread attention from foreign scholars. The American Academy of Marketing Science has included it as a priority object in its research agenda, and internationally renowned advertising and consulting firms have also maintained a high level of interest in this topic. At present, the research on this topic is not concentrated in the domestic academic community, but scattered in a number of disciplines and fields.

(2) Emotional Memory: The Development of Group Symbols

In the discussion of the results of interactive rituals, Collins proposed group symbols. However, since the whole process of five-movement rituals "the high degree of emotional connectedness one-by-one collective excitement is short-lived, and the duration of solidarity and emotional states in rituals often depends on the transition from short-term to long-term emotions, i.e., on the state of emotional reserves in the symbols that can evoke them again." This "state of reserve" is in part reflected in the "emotional memory".

The "emotional memory" in the ritual chain of Weibo interaction is formed by the "group symbols" condensed in the heart of the public, and this memory is not "static" but "dynamic" with the emergence of new scenes and rituals. Emotional memories are integrated into the daily issues of Internet users, making emotional interactions appear to be linked. Under the influence of the five-movement ritual chain, the collective memory contains the "emotional memory" shared among the members of the ritual. When similar events regain public attention, the "emotional memories" buried in people's hearts will be mobilized, and a scene of familiar "interactive rituals" will be staged.

Conclusion

With the increase of information transparency and public discourse, the emotional value of mass media represented by Sina Weibo has been paid more and more attention. This paper studies the emotional expression on Sina Weibo from a media-dependent perspective, and explores the communication and social values behind their emotional expressions with the help of artificial neural networks and their improved GUR-LSTM and LSIN-LSTM algorithms, and the study mainly draws the following two conclusions:

(1) Sina Weibo users mainly use "multiple symbols" and "text" to express emotions, while "picture" and "audio" are used less frequently, accounting for 0.1%. audio" are used slightly less frequently, accounting for 0.1% of the total. This indicates that the current expression of emotion on Sina Weibo mainly relies on text communication. However, after the implementation of the government's debugging policy, the public's emotions will either become more positive or more negative as the connotation of the incident is further explored. Therefore, the guidance of public opinion on Weibo is crucial.

(2) At a significance level of 0.1, the asymptotic significance of the Sina Weibo emotion score model is 0.218, and the asymptotic significance level in the emotion media is 0.572, i.e., the regression coefficients of each explanatory variable are significant. Studying the relationship between it and the level of economic development reveals that the higher the level of economic development, the more negative emotions the public has, and among them, the higher the dependence on the media, the higher the participation in public events, and the more complex the dimensions of emotional expression.

REMITTANCES REVIEW

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