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Covid-19 Disinformation and Public Perceptions: Empowering Affective Analysis through Large Language Model

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Abstract: Social media is flooded with disinformation about outbreaks, and emotional and ideological appeals can significantly influence public opinion more than objective facts. This study delves into the cognitive and affective responses of the public when confronted with disinformation about the Covid-19 epidemic on Weibo. To cope with the complexity of emotions, we designed a multidimensional complex affective space to depict the intricate cognition of the public. Drawing from human thinking processes, we proposed a fine-tuning method based on the large language model ChatGLM2-6B to augment semantic information and bolster the sentiment analysis capabilities of the large language model. The experimental results indicated that incorporating semantic information enhances the prediction accuracy of the large language model, with varying effects across different sentiment dimensions. Moreover, we analyze the public's topics concerning epidemic disinformation, and the findings demonstrate that the public tends to generate similar topics for such fake news. Emojis have emerged as a means for individuals to supplement the expression of complex emotions.

Keywords: affective computing; epidemic disinformation; large language model; semantic information; topic analysis; public opinion

1. Introduction

Since the beginning of 2020, Covid-19 has caused severe disruptions to people's regular lives, and people have become more sensitive to strong negative feelings about unconfirmed news spreading unchecked in social media [1]. This phenomenon has led to minor real-world issues being magnified through the information dissemination, easily making a significant influence on the public. Such information which shapes people's perceptions, is known as an information barrier. Information barriers encompass three types: disinformation, propaganda, and misinformation [2]. Disinformation refers to deliberately spreading false information, propaganda involves presenting one-sided information to influence the public, and misinformation denotes disseminating non-subjective false information on social media. During an epidemic, disinformation and misinformation are the most common information barriers people encounter. Disinformation often evokes strong emotions and prompts irrational comments. leaving individuals confronted not only with the disease itself but also with an "infodemic" in the information space [3,4], where claims such as "Delta and Omicron are co-circulating or recombining in northern China", "Drinking high levels of alcohol can protect against the new coronavirus," and "Repeated virus infections are positive because you do not change your toothbrush" circulate.

Due to the limited nature of human cognition, it is difficult for people to distinguish these highly confusing disinformation. When exposed to disinformation about the epidemic, they are prone to various emotions such as doubt, worry, fear, and anger [5], which may even lead to various symptoms, including fatigue [6], stress [7], and insomnia. When faced with disinformation and plunged into self-doubt, human beings generate mixed and complex affect, and traditional sentiment classification models are difficult to "understand" the emotions generated by human beings in a specific environment.

However, the large language model brings new opportunities for analyzing complex affect. The large language models have showcased remarkable proficiency in generating human-like text and participating in intricate conversational interactions [8,9]. This ability to understand and generate expressions can increase interpretability [10] in affective computation because sometimes we need to know what emotions people generate and why they generate them. Many scholars have begun to experiment with combining specific affective computing tasks with large language modeling help. For example, Atmaja et al. conducted sentiment analysis experiments and found that, with the same dataset and a large model framework, the large model outperforms the small model in terms of performance [11]. Miah et al. proposed an ensemble model of transformers and a LLM that provides a solution for cross-lingual sentiment analysis [12].

Although some scholars have found that current large models still need to be more effective than proprietary models for fine-grained sentiment classification tasks [13], accomplishing accurate classification tasks is not the advantage of utilizing large language models for affective computation. While existing studies primarily focus on improving the accuracy of classifying single-dimensional sentiments (e.g. positive or negative polarity), they lack insight into why specific emotions arise in complex contexts. For example, they do not explain the cognitive mechanisms behind public reactions to disinformation. The robust comprehension and reasoning capabilities of large language models are tools for deeper affective analysis, such as for the implicit sentiment analysis, where sentiment cues are implicit and ambiguous, Hao Fei proposed a three-step cueing framework and an inference modification method to gradually infer implicit aspects, generate opinions, and ultimately determine sentiment polarity [14]. Of course, there are some limitations to the current large language model. In particular, large-scale corpora used for Pre-training Language Models (PLMs) exhibit sentiment imbalances and biases [15], which can potentially transfer to the sentiment analysis task. Notably, most existing studies on affective computing based on LLMs rely on English datasets or general-domain text. This neglects the unique linguistic and cultural contexts of Chinese social media during public health crises, such as the rapid spread of pandemic-related rumours and their specific emotional triggers. Using LLMs to analyse emotions expressed through language helps to bridge the gap in affective computing and aligns with human communication norms.

Therefore, to investigate the cognitive and affective responses of the public during the epidemic, we gathered data on disinformation, like fake news, and comments related to the epidemic from Chinese social media platforms. We attempt to answer the following questions:

● How can we investigate people's cognitive by affective computing within the complex sociality context input?

● Can rich semantic information enhance the performance of large language models in affective analysis?

The primary contributions of this article are as follows.

1) We propose a fine-tuning method for large models that analyzes complex affects, aiming to enhance the interpretability of the emotion computation process.

2) We developed a multidimensional affective description method to examine the cognitive and emotional responses of the public when they encounter disinformation regarding the epidemic.

The remainder of this paper is structured as follows. Section II provides an overview of the data collection and the methodology design, encompassing multidimension complex sentiment space design, and large model fine-tuning methods. Section III presents the experimental design, results, and topic analysis. Finally, in Section IV, we present the conclusion of our study, summarizing the findings and suggesting avenues for future research enhancements..

2. Materials and Methods

2.1. Data Collection

We focus on Weibo, a widely popular and highly influential platform in the Chinese information space. To collect blog posts and comments associated with epidemic disinformation, we constructed a distributed web crawler using the Scrapy-Redis framework. The source of our epidemic disinformation data is the China Internet Disinformation Platform (CIDP), an official website established by the Cyberspace Administration of China to disclose instances of disinformation. For each disinformation case, we crawled blog posts and comments for seven days before and after the event, covering the timespan from March 2020 to June 2023.

To ensure data quality, we conducted pre-processing by removing all URL links and texts with a length of less than eight from the text data. Duplicate texts were also removed from the social text. The resulting amount of text data is presented in Table 1. Furthermore, we manually labeled the crawled data to create a dataset named MultiD3, comprising 315 blogs and corresponding comments, with each labeled for the three emotional dimensions: stance, worry, and rationality. The annotated MultiD3 dataset is publicly available for reproducibility at https://github.com/UpcNlp/ComplexCognitiveAffectiveData.

Table 1 Data Statistic

Category	Data volume
Disinformation	483
Blog	2749
Comments	31759

To ensure reliability and efficiency, we adopted a two-stage annotation framework:

1) LLM-generated Initial Labels. First,three LLMs (GPT3.5, Claude3.5, and Qwen2.5-72B) were first used to generate multi-dimensional annotations for 300 raw blog-comment pairs. The prompt for the LLMs was "Please annotate the following comment regarding the disinformation surrounding the topic of 'Covid-19' across the dimensions of 'stance', 'worry' and 'rationality'." We then calculated the Fleiss kappa coefficient [16] among the three LLMs for the annotated samples, in order to evaluate whether the automatic annotations were sufficiently consistent.

2) Human-in-the-Loop Refinement. A team of three human annotators reviewed and corrected the labels generated by the LLMs. Discrepancies were resolved through consensus voting, with ambiguous cases deleted.

2.2. Multi-dimensional Complex Affective Space

Emotional complexity is often characterized by emotional differentiation and emotional interdependence [17]. Emotional differentiation refers to the diversity of human emotions [18] or the continuous refinement of emotions into more nuanced states [19], while emotional interdependence highlights the continuous interaction between different emotions [20]. Traditional emotion theories often utilize the two dimensions of positive and negative emotions to explain human emotional experiences. However, in the face of the intricate human emotional system, these dimensions alone cannot fully capture the complexity of emotional changes, such as feelings of awe or skepticism. In order to better analyze the public cognitive and affective responses when confronted with disinformation about the epidemic, we have designed a multidimensional approach to describe emotions under complex contexts:

1) We consider the public's expressed stance in their comments as the first dimension of emotion description, recognizing that potential ambivalence significantly triggers complex emotions.

2) Due to th e widespread panic and persistent worry induced by the epidemic, which can lead to various psychological disorders like insomnia and anxiety, we incorporate the degree of emotional tension, precisely the dimension of "worry," as the second aspect of emotion description.

3) Considering that disinformation about the epidemic often elicits excessively aggressive comments, we introduce rationality as the third dimension to capture the affective aspect of responses.

Formally, we define the complex sentiment description method as the Complex Affective Space (CAP), represented as $CAP = D_s, D_w, D_r$, where D_s denotes the stance dimension, D_w represents the emotional worry dimension, and D_r represents the rationality dimension. Given a set of comment data $C = c_1, c_2, \cdots, c_n$ associated with the epidemic disinformation S_D, we employ a large language model to predict the results $R = R_s, R_w, R_r$ in the dimensions of D_s, D_w, and D_r, respectively. The computation process is depicted in Eq. 1.

$$R = \bigcup_{j \in \{s.w.r\}} \sum_{i=1}^{n} Finetune_j(S_D | c_i) \tag{1}$$

Finetune refers to the method of fine-tuning the large language model, with detailed information provided in the next subsection. The results in the D_s dimension was categorized as "supportive, opposing, and neutral," while the D_w dimension was classified as "anxious and relaxed," and the D_r dimension was divided into "rational and irrational." Specifically, we employed binary categories (anxious and relaxed) to succinctly describe people's emotional states. Although there may be transitional states where emotions fall between anxiety and relief, binary emotions remain effective in capturing individuals' primary responses to disinformation in this context. Hence, binary categorization is more suitable in terms of simplicity and expressive accuracy. Similarly, the rationality dimension was categorized as rational and irrational.

2.3. Semantic Enhancement-based Fine-tuning of Large Language Models

To enhance the interpretability of the affective computing process, we emulate human thinking and propose a large model fine-tuning method based on semantic enhancement. In a sentiment computing task, the model is not solely reliant on input information for predictions. Instead, the model is expected to engage in independent thinking and generate task-relevant information to support the final decision-making process. We begin by transforming the analysis of cognitive and affective responses in the context of epidemic disinformation into a classification task, denoted as $\mathcal{D} = (x_i, y_i)$. Given a natural language input x_i, we leverage the In-Context Learning (ICL) capability of the large language model to construct a set of instances, denoted as $\mathcal{S}_{demos} = (x\prime_j, y\prime_j)_{j=1}^{N}$. The large language model predicts the label y_i by learning the relevant knowledge from the examples, and the overall prediction process is shown in Eq. 2.

$$\arg\max_{(x_i,y_i)\in\mathcal{D}} P_{LLM}\left(y_i|x_i, S_{demos}\right) \tag{2}$$

Where P_{LLM} represents the probability of y_i given the demonstrations and x_i. However, this contextual learning approach, although beneficial for the model to grasp task patterns, does not fully harness the knowledge encoded in the extensive parameters of the large model. It also does not enable the model to proactively contemplate the information that is directly relevant to the inputs and contributes to task processing. To address this limitation, we extend the In-Context Learning (ICL) framework by facilitating the generation of supplementary information, denoted as $I_{external}$, which directly pertains to the task and aids decision-making. The overall prediction process is outlined in Eq. 3.

$$\arg\max_{(x_i,y_i)\in\mathcal{D}} P_{LLM}\left(y_i|x_i, S'_{demos}, I_{external}\left(LLM(x_i)_{k=1}^{M}\right)\right) \tag{3}$$

Where $LLM(x_i)_{k=1}^{M}$ denotes the additional information related to the task and generated by the large model itself, with M representing the dimension of the additional information. S'_{demos} represents the demonstrations composed of the extra information. Leveraging the multidimensional complex emotion space, we determine the user' s emotional response by detecting their stance, worry, and rationality dimensions. For instance, considering the stance dimension, we leverage the popular theory that human short-term memory capacity is 7 ± 2. As a result, we design seven pre-generated semantic information items directly relevant to stance detection. These items serve as semantic information to support the final prediction task, and their specific details are provided in Table 2.

Table 2 Semantic Information

Abridge	Category	Support Aspect
AS	Argument Structure	Analyzing the argumentative structure of the text to see if it provides clear arguments and logical reasoning.
KK	Keywords and key ideas	Identify key words and key ideas addressed in the text
CB	Contextual background information speculation	Speculate on the context and background information of the text, including author, source, time, and place.
EC	Emotional coloring of the text	Analyze the emotional coloring of a text, including the author's expression of positive, negative, or neutral emotions about an idea or topic.
SR	Language style and rhetorical devices	Pay attention to the linguistic style and rhetorical devices of a text, including the use of similes, metaphors, rhetorical questions, etc.
SS	Sentence structure analysis	Pay attention to the grammatical structure of the text and sentence expressions. For example, use of negatives, comparisons, emotional vocabulary, etc.
KI	General knowledge inference	Using common sense and general observation, attempt to understand whether ideas in a text match known facts or general knowledge.

3. Results and Discussion

3.1. Data Analysis

Firstly, we conducted topic analysis on the entire crawled dataset using a text clustering method, which was detailed in our previous work [21]. The resulting topic clustering results are partially shown in Figure 1, with orange representing the topic words after removing Emoji and blue indicating the topic words containing Emoji. The number indicates the probability of the topic appearing in the comments.

It was observed that when confronted with disinformation about the epidemic, people engaged in discussions on topics with inter-topic solid correlation, demonstrating a certain level of emotional vigilance.

Additionally, we noticed that the public tended to employ emojis to complement the expression of complex emotions, compared to text alone. Out of the 31,759 crawled data points, 11,828 contained Emoji, with 3,140 of them consisting solely of Emoji.

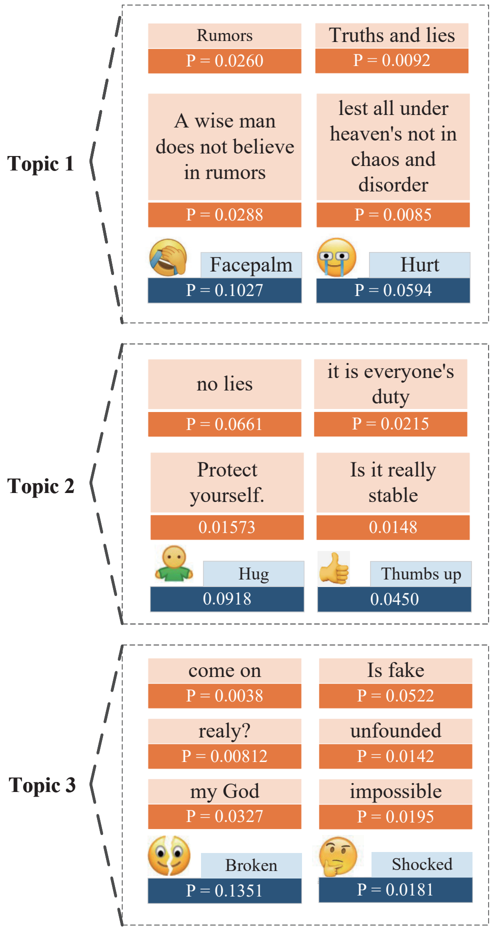

Figure 1. Topic clustering results.

3.2. Experimental Design

Based on the multi-dimensional complex emotion space, we employed the ChatGLM2-6B [22] large language model to analyze the intricate emotions associated with epidemic disinformation. These emotions were evaluated across three dimensions: stance, worry, and rationality. Additionally, to determine the significance of specific additional semantic information in facilitating active thinking within the large language model, we conducted orthogonal experiments to evaluate the importance of semantic information.

Initially, we treated each semantic information as a variable and assigned two levels (yes or no) based on whether the variable was utilized during training or testing. Subsequently, an $L\left(2^8\right)$ table was selected to facilitate the design of an orthogonal experiment, and the specifics of the experimental design can be found in Table 3. In the table, 1 indicates that the semantic information is included during training or testing, while 0 indicates its exclusion.

Table 3 Orthogonal Experimental Design

ID	AS	KK	CB	EC	SR	SS	KI
1	1	1	1	1	1	1	1
2	1	1	1	0	0	0	0
3	1	0	0	1	1	0	0
4	1	0	0	0	0	1	1
5	0	1	0	1	0	1	0
6	0	1	0	0	1	0	1
7	0	0	1	1	0	0	1
8	0	0	1	0	1	1	0

The ChatGLM2-6B model was fine-tuned using the ptuning method through multiple rounds of dialogs. The learning rate was set to $2e^{-2}$, the maximum length of the inputs was 2048, and the maximum length of the outputs was 256. Accuracy metrics were employed to evaluate the performance of the model.

3.3. Experimental Results

First, we verified the effectiveness of using ChatGLM2-6b for multidimensional complex affective computation without additional semantic information, as shown in Table 4.

Table 4 Results without semantic information

Dimension	Accuracy before fine-tuning	Accuracy after fine-tuning
Stance	0.3667	0.4333
Worry	0.6444	0.7222
Rationality	0.4222	0.5889

Subsequently, we examined the impact of various semantic information on the stance dimension in both blog posts and comments, as presented in Table 5.

Table 5 Stance dimension results under different experiment numbers

ID	1	2	3	4	5	6	7	8
Acc (Before)	0.31	0.38	0.36	0.31	0.34	0.34	0.42	0.35
Acc (After)	0.26	0.38	0.38	0.43	0.36	0.35	0.44	0.38

By comparing Table 4 and Table 5, it can be seen that when there is no semantic information, fine-tuning has limited improvement on Stance (+0.06), Worry (+0.07), and Rationality (+0.16). However, after adding semantic information, the fine-tuning accuracy improves for stance (e.g. ID 4: 0.43, ID 7: 0.44), and the distribution becomes more stable (the difference between IDs $\leqslant$ 0.18). This indicates that semantic integration significantly improves the robustness of stance detection.

In the experiments with AS in Table 5 (IDs 1, 3, 4), the fine-tuned accuracy on the Stance dimension is $\geqslant$ 0.38 (ID 4: 0.43), which is higher than that of IDs 5 to 8 without AS ($\leqslant$ 0.38). This suggests that a clear argument structure is key to judging stances: for instance, supportive comments often contain logical reasoning, while opposing comments tend to have a refuting structure.

We posit that enabling additional semantic information has a positive impact both before and after fine-tuning. This type of semantic information is considered beneficial in enhancing the model's effectiveness. Based on the significant differences observed for each type of semantic information, we select three semantic information types, "keywords and key ideas", "emotional color of the text", and "linguistic style and rhetorical devices", to aid the large language model in stance detection between blog posts and comments.

In addition, we evaluated the effect of different additional semantic information on the stance detection task after fine-tuning, as shown in Table 6. Orthogonal experiments show that the KK is the most crucial semantic feature for stance detection (After Range = 0.06). When the model uses "keywords and key ideas" (KK = 1), stance detection accuracy increases from 0.34 to 0.41, representing the greatest improvement. This is in line with the intuitive logic of stance detection. In other words, people's stance attitudes in comments are mostly expressed through direct keywords (such as "I support the blogger", stance "support"), rather than complex argumentation structures (AS) or general knowledge inference (KI).

Table 6 Analysis of the results of orthogonal experiments on positional dimensions between blog posts and comments

Semantic Variables		AS	KK	CB	EC	SR	SS	KI
	0	0.34	0.34	0.36	0.36	0.34	0.33	0.34
Before	1	0.36	0.36	0.34	0.35	0.36	0.38	0.36
	Range	0.02	0.01	0.02	0.01	0.02	0.05	0.01
	0	0.36	0.34	0.37	0.36	0.35	0.36	0.37
After	1	0.38	0.41	0.38	0.39	0.40	0.39	0.38
	Range	0.02	0.06	0.01	0.02	0.05	0.03	0.01

Same as Above, we evaluated the effect of different semantic information on the worried dimension, as shown in Table 7 and Table 8. The results of the orthogonal experiments indicate that including semantic information like "contextual and background information speculation", "linguistic style and rhetorical devices", "correlation analysis between blog posts and comments", and "general knowledge inference" leads to enhanced prediction accuracy for the worry dimension in large language modeling analysis.

Table 7 Results of commenter-worry dimension analysis under different experiments

ID	1	2	3	4	5	6	7	8
Acc (Before)	0.46	0.66	0.56	0.57	0.38	0.56	0.46	0.54
Acc (After)	0.24	0.55	0.60	0.51	0.73	0.50	0.66	0.64

The experimental results for the 'Worry' dimension show that before fine-tuning, the model mainly relied on direct emotional words, resulting in limited accuracy. After fine-tuning, general knowledge Inference (KI, After Range = 0.15) and Argumentation Structure (AS, After Range = 0.15) became the core semantic dimensions. The model achieved an optimization from "superficial emotion capture" to "logic-commonsense-driven emotion understanding" by verifying the factual rationality of worries and analyzing their logical arguments. Meanwhile, Language Style and Rhetorical devices (SR, After Range = 0.12) and Sentence Structure analysis (SS, After Range = 0.04) assisted in capturing emotional details in language, further enhancing the accuracy stability. For example, in Table 7, for ID 7, After = 0.66, an increase of 0.20 compared to Before. This multi-dimensional semantic integration (KI + AS + SR + SS) significantly enhanced the worry detection ability. After fine-tuning, the accuracy of ID 5's accuracy reached 0.73, 1.9 times that of Before, verifying the synergistic effect of commonsense and logic. Relying on a single emotional feature alone makes it difficult to achieve such deep integration.

Table 8 Comments on the analysis of the results of orthogonal experiments on Worry dimensions

Semantic Variables		AS	KK	CB	EC	SR	SS	KI
	0	0.56	0.52	0.53	0.47	0.53	0.49	0.51
Before	1	0.49	0.53	0.52	0.58	0.52	0.56	0.54
	Range	0.07	0.01	0.01	0.11	0.01	0.07	0.02
	0	0.47	0.51	0.52	0.56	0.49	0.53	0.48
After	1	0.63	0.60	0.58	0.55	0.61	0.58	0.63
	Range	0.15	0.09	0.05	0.01	0.12	0.04	0.15

Finally, we evaluated the effect of additional semantic information on detecting the degree of rationality of a comment, as shown in Tables 9 and 10. The experimental results indicate that the model accuracy improved in all the experimental scenarios after fine-tuning. According to the findings from the orthogonal experiments, we posit that "correlation analysis between blog posts and comments" can assist the large model in analyzing the rationality of commenters.

Table 9 Results of the analysis of the rationality dimension of comments under different experiments

ID	1	2	3	4	5	6	7	8
Acc (Before)	0.40	0.46	0.46	0.51	0.30	0.51	0.43	0.46
Acc (After)	0.53	0.50	0.50	0.43	0.52	0.48	0.52	0.44

Table 10 Comment on the analysis of the results of orthogonal experiments on rationality dimensions

Semantic Variables		AS	KK	CB	EC	SR	SS	KI
	0	0.46	0.41	0.44	0.40	0.46	0.41	0.46
Before	1	0.42	0.46	0.44	0.48	0.42	0.46	0.42
	Range	0.03	0.05	0.005	0.08	0.03	0.05	0.03
	0	0.49	0.51	0.49	0.51	0.49	0.48	0.49
After	1	0.49	0.47	0.48	0.46	0.49	0.50	0.49
	Range	0.002	0.03	0.01	0.05	0.01	0.02	0.002

Drawing from the findings of the orthogonal experiments, we identified the semantic information that exhibited a more substantial improvement effect on different emotion dimensions. The filtered results are presented in Table 11.

Table 11 Influential semantic information filtered

The Emotional Dimension	Semantic information
Stance detection between blog posts and comments	Keywords and key ideas; emotional coloring of the text Language style and rhetorical devices
Degree of tension of commenters	Contextual and background information speculation Language style and rhetorical devices Linking analysis between blog posts and comments General knowledge inferences
Degree of theory in commenters	Correlation analysis between blog posts and comments

3.4. Social Mask, Emotional Manipulation, and the Limits of Algorithmic Empathy

While this study demonstrates that large language models (LLMs) can approximate complex human emotions through cognitive-inspired fine-tuning, a critical question remains: can LLMs truly understand affect, or are they merely replicating its linguistic surface? In high-context social media environments like TikTok, X, and Weibo, emotional expression is often governed by what might be described as a "social mask"—drawing on Goffman's [23] dramaturgical framework where individuals perform to manage the impressions others form of them. According to Goffman, social interactions are akin to theatrical performances where individuals act to maintain social face, suppress vulnerability, or present a socially acceptable image. This concept is particularly relevant in collectivist cultures, where overt expressions of distress or dissent might be concealed behind humor, sarcasm, or strategic emojis. Our model, while effective at decoding explicit emotional signals, struggles to interpret these emotionally strategic facades, which are culturally ingrained.

This introduces a significant challenge for LLMs: despite their ability to parse complex linguistic data, they may fail to perceive the intentional emotional layers that are so fundamental in human interaction. As Foucault argued in "Discipline and Punish" [24], individuals are constantly subject to subtle forms of regulation—be it through societal expectations, social norms, or media platforms—that shape not only their outward behavior but also their internal emotional responses. In this sense, emotional expression on social media is not just an individual's personal reaction, but a strategic performance shaped by power structures. The ability of LLMs to detect and decode emotions, therefore, is limited by their lack of embodied understanding—they are parsing textual data without the context of the power relations and social scripts that underlie human communication. While LLMs might excel at recognizing surface-level emotional cues, they struggle to penetrate the deeper, more strategic layers of human emotion.

Furthermore, our findings regarding the amplification of emotional content via emojis shed light on the affect-algorithm nexus—a new form of emotional manipulation enabled by platform algorithms. Studies have shown that emotional content tends to spread more rapidly than neutral or fact-based information [25,26], and our research supports this claim, revealing that multimodal posts containing emojis are more likely to be shared. This suggests that social media algorithms are not neutral—they actively promote emotionally engaging content that can optimize user interaction, irrespective of its factual accuracy. This creates a paradox: while LLMs can help us understand emotions with greater precision, they are simultaneously part of an ecosystem where emotional engagement is weaponized for virality.

4. Conclusions

The outbreak of the Covid-19 epidemic disrupted people's regular social life, and this real-life upheaval intertwined with the chaos of the information space as various forms of epidemic disinformation emerged, continually challenging individuals' cognition. In this study, we employed fine-tuning techniques on a large model to analyze people's cognitive and emotional responses when confronted with complex scenarios, such as epidemic disinformation.

Unlike traditional text categorization, we integrated comment data within the context of disinformation, making the input more intricate and reflective of natural social environments. To address the complexity of the human emotional system, we constructed a complex emotional space based on three dimensions: stance, worry, and rationality. Additionally, we proposed a fine-tuning method that enriches semantic information by emulating human thinking. We designed three-dimensional orthogonal experiments involving seven types of semantic information, revealing that augmenting different semantic information can enhance the prediction accuracy of the large model. Furthermore, we conducted a thematic clustering analysis on the crawled data, and the results demonstrated a strong correlation among the topics generated by the public regarding epidemic disinformation. Interestingly, the public used Emojis to complement the expression of complex emotions.

Nevertheless, we acknowledge that our manually specified semantic information could benefit from further refinement to mitigate potential bias introduced by manual experiences. Moreover, improvements in the design of the Complex Affective Space are necessary to leverage large generative language model, enabling a more comprehensive explanation of the complex human emotion system through natural language.

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Data Availability Statement: The data supporting the findings of this study are openly available at [https://github.com/UpcNlp/ComplexCognitiveAffectiveData].

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