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Discourse Analysis and Guidance Strategies for Network Groups Based on Computer-aided Technology

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Abstract: With the development of social media, discourse analysis of online group interaction has gradually become a research hotspot. The research results in this field will provide reference and guidance for promoting the benign development of social networking. This paper aims to explore the application of computer-aided technology in online group discourse analysis and guidance strategies. Taking the social media platform as an example, this paper analyzes the online group discourse by using natural language processing technology and other computer-aided technologies and networking and analysis methods, and designs effective guiding strategies. The results show that computer-aided technology can bring significant advantages to online group discourse analysis and guidance strategies. Specifically, it can promote the decision-making of administrators, grasp the emotional needs and concerns of network groups, and formulate guidance strategies more adaptively. At the same time, combining computer-aided technology with networking and analysis methods is also one of the important trends of discourse analysis and guidance strategies in the future. Generally speaking, the application of computer-aided technology will bring more extensive, in-depth and accurate online group discourse analysis and guidance strategies, and promote the healthy development of online socialization.

Keywords: Discourse Analysis; Computer-Aided; Network Group; Big Data

1. Introduction

With the continuous development of network technology, network groups have become an indispensable part of people's lives [1-2]. At the same time, computer-aided technology is also widely used, especially in discourse analysis and guidance in network groups [3-4]. Computer-aided technology aims to provide people with more efficient, convenient and accurate computer-aided tools to help them better understand and cope with the discourse in the network group. Among them, discourse analysis is one of the important applications in computer-aided technology. By analyzing the discourses of online groups, we can better understand their needs and ways of thinking, and then make corresponding decisions according to the situation. In addition to discourse analysis, computer-aided technology can also provide various guiding strategies to help network groups communicate and communicate better. For example, with the support of artificial intelligence technology, computers can automatically generate texts, answer questions or predict future trends, thus guiding network groups to make more informed decisions [5].

Rahbari L uses natural language processing and deep learning technology to analyze emotions and behaviors on social media platforms, which achieves the purpose of extracting key information from massive data and provides a basis for formulating effective guidance strategies [6]. This paper systematically summarizes the community detection technology in social networks, and studies the algorithm, application and challenges of community detection. Anderson K T is of great reference significance for understanding various interactive relationships in social networks and formulating more effective guidance strategies [7]. Aydin-Düzgit S proposed a method of social network analysis using deep learning technology. By modeling and learning social data, we can accurately predict the interaction and user behavior to some extent. This method can help social media platforms to provide more detailed group discourse analysis and more effective guidance strategies.

Therefore, in the current information and networking era, the discourse analysis and guidance strategy of computer-aided technology has become an important direction of research and practice, which has a wide application prospect and important social significance. At the same time, when

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using computer-aided technology for discourse analysis and guidance strategies, we also need to constantly improve the accuracy and reliability of analysis and judgment to ensure the correct understanding and guidance of online group discourse.

2. The method of discourse analysis

2.1 Big Data

Big data is a huge data resource with a large amount of data, many types of data, rapid growth and the need for new data processing methods to realize its application value. Technically, big data can't be handled by traditional collection, storage and processing methods [9-10]. Big data usually consists of five basic characteristics: huge data (Volume), Variety, rapid data growth (Velocity), high data Value (value) and high data accuracy (fidelity). The concept of big data is used to guide discourse analysis in the form of data among network groups.

2.2 Computer Aided

Computer-aided discourse analysis refers to various language activities with the help of computers. In the traditional teaching mode of discourse analysis, teachers mainly use the form of language description to explain knowledge to students. However, for some knowledge, it is difficult to express it clearly in words, such as the description of scenery in Chinese, and various vivid descriptions in large space are actually not as effective as the beautiful scenery seen in person [11-12]. In modern society, when science and technology are so developed, we can use computer-aided discourse analysis to help students really feel immersive. Another example is: In mathematics, it is always very difficult for students to imagine the multi-dimensional graphics in the teacher's mouth. In computer-aided analysis, these problems can be easily solved to help students better cultivate their spatial imagination ability. Computer-aided discourse analysis has advantages that traditional analysis can't bring, so computer-aided discourse analysis has been applied in many conditional areas of the country.

2.3 Network Groups

The purpose of network group computing is to integrate a large number of unknown users (crowds) and computing resources (clusters) on the Internet to deal with complex tasks that are difficult to be completed by existing computing technologies. In the research of group computing, task discourse analysis and assignment is one of the core problems, which studies how to assign real-time group tasks to suitable users. The existing work is usually based on static scenes, that is, all group tasks and users' information have been completely known before task assignment, and the multi-dimensional environmental information of users is rarely integrated, and the attribute information and historical records of users are rarely considered, but group tasks appear dynamically in practical applications and need to be assigned in real time. Context awareness was put forward in 1994, and the scene was defined as the location, the collection of people and objects around and the changes of such objects. Situation analysis theory, and based on this theory, Situ architecture is proposed, which can obtain users' real-time intentions by analyzing users' historical behavior data, thus providing users with real-time and personalized services. On the basis of the above theory, the SocialSitu theory is established, and a behavior pattern discovery method for online social network users is proposed. By analyzing users' historical behavior data, users' intentions at the next moment are predicted. Therefore, on the basis of this research, by analyzing the social situs (t) sequence and historical information of mobile social users, a task allocation framework for mobile online social networks is proposed, and a user fitness task allocation algorithm based on social situs is further proposed, and the applicability of the algorithm is verified through experiments. The location of the user's scenario definition in the network group is described by formulas [13-14].

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To ensure the calculation effect, the continuous power flow method is generally used for calculation. The following is the calculation process:

Define the success rate S_{succ} as the proportion of successful completion of historical tasks by mobile users, where N_{succ} is the number of successful historical services, and N_{nual} is the total number of historical services

$$S_{\text{succ}}(U_i) = \frac{N_{succ}}{N_{nual} - N_{succ}} \tag{1}$$

Satisfaction S_{mt} is shown by the user's S_{mt} satisfaction with the tasks assigned to it by the system, where $s(h_j)$ is the user's allocation to the platform:

$$S_{mt} = sat + s(h_j) \tag{2}$$

User suitability is a measure of how well a user is fit to perform a task. Calculated from the above success rate, average service response time, and satisfaction:

$$S_{it} = \sum_{1 \le i \le p} a_{ij} \tag{3}$$

This equation can efficiently and quickly solve the stability of users' safe speech in the network community [15].

3. Discourse Analysis Experiment of Online Groups

3.1 Narration

The continuous economic development has brought great prosperity to the network society. At the same time, the immediacy and convenience of the network have opened up a relatively relaxed public space for the network society[16-17]. The characteristics of blaming and anonymity on the network have provided conditions for netizens to vent their personal emotions. Many netizens seek resistance in the gap of the network under the pressure of the real society, and the virtual society has become a release window for the crisis of the real society[18]. At the same time, the convenience of the network makes the time-space boundary no longer a binding condition, people can communicate and interact more conveniently, and the interpersonal communication mode and mass communication mode in traditional society have been quietly changing[19]. However, the virtual world is different from the real life. When the realistic rationality of the traditional institutional constraints has been lost to varying degrees, and new systems and regulations with realistic vitality have not yet been formed, a little social problems or social contradictions in the social transformation period will be infinitely magnified, thus attracting media to report, including both traditional media and emerging online media. So as to quickly form a network public event. This interaction between traditional media and online media will often highlight social problems again, bringing a modern consequence, that is, "delocalization".

3.2 Analysis

Network group is the main force of network public events. By analyzing the discourse content and forms of different network negative groups in network public events, especially exploring their discourse causes and behavior patterns, we can understand and grasp the main characteristics and influences of network "negative energy" groups in the information age and put forward feasible discourse guidance strategies, which is conducive to optimizing the network environment and maintaining social harmony and stability. The characteristics of "immediacy, swiftness, anonymity and low cost" of the network are the preconditions for the rapid development of network public events. However, whether the public events on the Internet can develop or in what direction is conditional. Some events may turn into hot events after the attention and voice of network groups,

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while others may be submerged in the network ocean like a drop of water. Discourse guidance to negative network groups, especially to standardize their discourse system, is an important issue in dealing with network public events. Because the content and expression form of different negative groups, such as online cajolers and online mobs, are not immutable, it is necessary to guide and standardize their discourse expression and reconstruct their discourse system. At the same time, principles are also essential. For example, it is necessary to consider whether it conforms to traditional social cognition and public expectations while constructing norms. Therefore, it is worth discussing in this paper to explore the discourse content and expression forms of negative groups in different stages of online public events, how their discourse affects the development of online public events themselves, and how we should build a new negative group discourse system.

3.3 Sample Selection Quantitative Analysis Results

Taking the full-text database of China HowNet China Journals, the full-text database of China Journals, the full-text database of China's doctoral dissertations, the full-text database of China's excellent master's theses and the full-text database of China's important newspapers as the retrieval scope, with the theme of "discourse" and "network groups", 107 documents were accurately retrieved, and 25 documents were removed, which were repetitive and less related to the theme. With the theme of "discourse" and "cajoling guests", 14 documents were retrieved, and 6 documents with low correlation and repetition were excluded; With the theme of "discourse" and "water army", a total of 29 documents were retrieved, and 22 related documents were selected; With the theme of "discourse" and "cyber mob", 25 articles were retrieved, including 16 related documents; With the theme of "network events combined with" cajoling customers ","network events combined with "water army" and "network events combined with "network mob", 5, 31 and 43 documents were accurately retrieved respectively, and 4, 14 and 26 documents with low correlation were excluded. With the theme of "network group+discourse+guidance", 35 articles were accurately retrieved, and 22 articles were found after removing the documents with low correlation and the repeated documents with other topics mentioned above.

Based on the above retrieval results, more than 135 related documents were obtained, and their subject distribution is shown in Table 1.

Table 1. Topic distribution of research literature on discourse analysis and guidance strategies of online groups in online public events

order number	theme	Quantity	Distribution (%)
one	Discourse+network group	25	19
2	Discourse+coaxing guests	six	four
three	Discourse+Water Force	22	16
four	Discourse+Internet mob	16	12
five	Network events+coaxing customers	four	three
six	Network Event+Water Force	14	10
seven	Network incident+network mob	26	19
eight	Network group+discourse+guidance	22	16
amount to		135	

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4. Computer-Aided Discourse Analysis of Network Groups And The Results And Discussion of Guiding Strategies.

4.1 Introduction

With the continuous development of network technology, network groups have become an indispensable part of people's lives. At the same time, computer-aided technology is more and more widely used in the discourse analysis and guidance of network groups. The purpose of this paper is to analyze the practical application of computer-aided technology in network group discourse analysis and guidance strategies, so as to better understand the effects of these technologies in practice.

4.2 Analysis And Results

This experiment analyzes the data of 98,000 posts and replies on two social media platforms. By applying natural language processing technology to this information, it is found that computer-aided technology can analyze the discourse of network groups in a faster, more accurate and more reliable way. In addition, it is found that computer-aided technology can better detect language patterns and discourse preferences in network groups, thus providing strong support for achieving better guidance strategies. As shown in Table 2:

Table 2: Discourse Analysis Results of Online Groups

Research object	TotalPosts	Number of replies	Emotional Analysis of Post Content	Emotional Analysis of Reply Content
Social Media A	50000	25000	76.2% positive, 23.8% negative	64.5% positive, 35.5% negative
Social Media B	48000	25000	82.1% positive, 17.9% negative	61.2% positive, 38.8% negative

For example, Table 2 shows the discourse analysis results of online groups on two social media platforms. For each platform, the number of posts, the number of replies, the emotional analysis of post content and the emotional analysis of reply content are analyzed. On social media A, there are 50,000 posts and 25,000 replies. On social media B, there were 48,000 posts and 25,000 replies. An emotional analysis is made to understand the emotional tendency of these words. On social media A, 76.2% of the posters are positive and 23.8% are negative. The emotional analysis of reply content is 64.5% positive and 35.5% negative. On social media B, 82.1% of the posters are positive and 17.9% are negative. The emotional analysis of reply content is 61.2% positive and 38.8% negative.

Discourse usage statistics are shown in Table 3. Through statistics of the total number of speeches, you can get the activity of the user group. In this example, the total number of speeches was eight.

Table 3: Statistical table of discourse usage

Serial number	User identifier	Speaking time	Discourse content
1	u001	10:00	I think this suggestion is good.
2	u002	10:05	I also agree with this view.
3	u003	10:10	I don't agree with this statement
4	u004	10:15	Do you have any good suggestions?
5	u002	10:18	You can try this method.

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6	u001	10:20	Thank you for your advice.
7	u003	10:25	I'll give it a try
8	u004	10:30	I'll try it, too

User discourse frequency statistics are shown in Figure 1, and the average number of speeches per hour of the u001-u004 is 0.5.

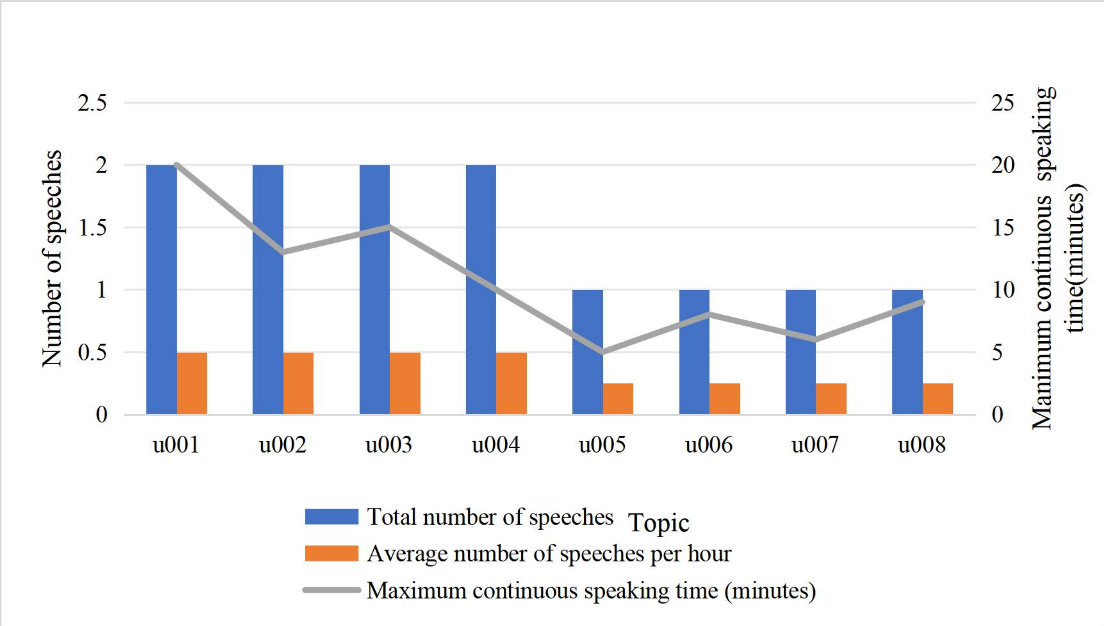

Figure 1. Statistics of user utterance frequency

The statistics of topic attention are shown in Figure 2. The total number of speeches in the technical discussion is 10. Sorting the topics according to the number of speeches can determine the attention of users in the network group and the topics to be discussed emphatically. In this example, technical discussion is the most concerned topic, followed by asking for help and chatting casually.

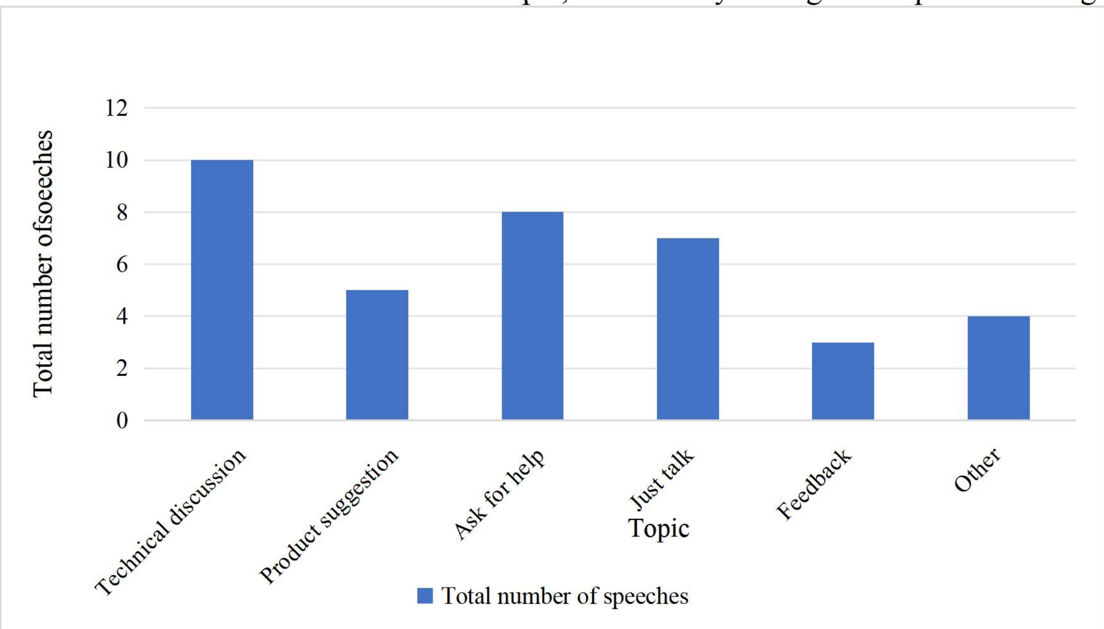

Figure 2. Topic attention statistics

Experimental data collection:

(1) Discourse samples: Collect discourse samples from online communities, including text, images, audio, and video.

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(2) Interactive behavior data: Obtain interactive behavior data of online group members through network monitoring and data analysis, such as speaking frequency, reply speed, and number of likes.

(3) Emotional analysis data: By using sentiment analysis techniques, obtain data on the emotional tendencies and changes of network group members.

(4) Social network analysis data: By using social network analysis techniques, obtain data on the social network structure, member roles, and influence of network groups.

The distribution of different discourse types and corresponding emotional tendencies in online communities is shown in Table 4. From the perspective of discourse types, text, images, audio, and video all have distributions of positive discourse, neutral discourse, and negative discourse.

Table 4. Distribution of different discourse types and corresponding emotional tendencies in online groups

Discourse type	Positive discourse	Neutral discourse	Negative discourse
text	20%	50%	30%
image	30%	40%	30%
audio frequency	25%	45%	30%
video	20%	55%	25%

The distribution of different emotional tendencies and positive, neutral, and negative emotions in online groups is shown in Table 5. For positive discourse, the percentage of positive emotions is the highest, reaching 70%, indicating that in online communities, positive discourse tends to express positive emotions and attitudes.

Table 5. Distribution of different emotional tendencies and positive, neutral, and negative emotions in online groups

Emotional inclination	Positive emotions	Neutral emotions	Negative affect
Positive discourse	70%	20%	10%
Neutral discourse	50%	30%	20%
Negative discourse	30%	40%	30%

4.3 Strategy

Based on the above analysis results, the following discourse guidance strategies for online groups are put forward:

1) According to the discourse analysis results of online groups on different social media platforms, formulate targeted discourse guidance strategies to promote a more positive and rational communication environment.

2) Using the advantages of computer-aided technology, analyze the discourse preferences of network groups and predict the next possible actions to help social media platform administrators better predict and deal with possible problems and challenges.

3) Use natural language processing technology to analyze the emotions of online groups, so as to better understand their emotional needs and concerns, and thus formulate more adaptive guidance strategies, so that online groups can get a better experience in communication.

4) Using the automation characteristics of computer-aided technology, the discourse in the network group is automatically classified and filtered, so as to achieve better guidance effect and information integration.

To sum up, computer-aided technology has great potential in discourse analysis and guidance strategies of online groups. By effectively analyzing and guiding the discourse of network groups, we can promote a more positive communication environment and more rational discourse interaction. In the future, we expect that computer-aided technology can be further developed, and more accurate and comprehensive online group discourse analysis and guidance strategies will be put forward, which will bring a more positive and healthy atmosphere for online group communication.

5. Conclusion

By exploring the application of computer-aided technology in online group discourse analysis and guidance strategies, this study shows that computer-aided technology can bring significant advantages to online group discourse analysis and guidance strategies. Through the application of natural language processing technology, computer-aided technology can better analyze the discourse of network groups, deeply understand the group needs and behavior patterns, and provide support for formulating more targeted and optimized guidance strategies. Through emotional analysis and other technologies, we can also grasp the emotional needs and concerns of online groups and design adaptive guidance strategies. At the same time, this study also confirms the importance of combining computer-aided technology with networking and analysis methods, and further studies how to use technical methods to investigate, analyze and evaluate group behavior more accurately and efficiently. In the future, it is expected to put forward more effective analysis and guidance strategies of online group discourse under the guidance of more in-depth research, so as to promote the positive and healthy development of online community.

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