# Decoding Patients' Voices: How Social Media Reviews Reveal the True Impact of Medical Service

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## *Abstract*

**Background:** An increasing number of patients are posting information about their medical experience on social media, which constitutes a valuable information resource with the potential to improve medical services and patients' medical experience.

**Objective:** By analyzing the content of patients' medical reviews posted on social media, this study aims to explore the aspects of medical services that users focus on, their focal points, emotional tendencies, and changing trends.

**Methods:** This study targets several top large general tertiary hospitals in China. It collects and organizes the text content of patients' medical experience reviews about these hospitals on a well-known domestic online review website. Using the text analysis software ROST CM 6.0 combined with Python programming, it conducts collection, high-frequency word analysis, semantic network analysis, sentiment analysis, and trend analysis of patients' online reviews.

**Results:** Patients pay the highest attention to the service attitude of medical staff and the convenience of medical treatment. The quality of medical services that patients care about centers on service attitude and service convenience, and extends to other related elements. Patients' emotional tendencies towards medical services are approximately half positive and half negative; positive emotions are concentrated in aspects such as appointments and hardware, while negative emotions are focused on process order and doctor-patient communication. Patients' concerns and emotional tendencies show certain regular changes over time.

**Conclusions:** Patients' online reviews focus on non-technical factors such as attitude, processes, and waiting time, with less attention to technical factors such as treatment effects. Positive and negative emotions each account for approximately half, with negative emotions slightly exceeding positive ones, indicating the impact of non-technical factors on the medical experience. While focusing on professional technology, top large medical institutions should also strive to improve service attitude, language communication, convenient processes, and medical experience. Analyzing online medical review content provides a new method and perspective for studying patient satisfaction and improving medical services.

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# Original Manuscript

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**KEYWORDS**
decoding; patients; voices; social media; reviews; impact; medical service; top; hospitals

***Introduction***

On third-party websites and platforms, users have posted a large amount of evaluation information about service providers. This information is a valuable asset and has been widely used in market and marketing links in the commercial field [1-2].

In the medical field, more and more patients are posting medical-related evaluation information through third-party online platforms. This information reflects patients' perceived medical service quality and emotional experience, and with its dissemination, it also affects other patients' choice of medical treatment [3-4]. Researchers believe that this information should be paid attention to and learned from, as it is a potential channel to improve the level of medical services [5-6]. Some researchers have begun to analyze and mine these user-generated online review contents to understand users' perceived service experience and emotional tendencies, thereby putting forward suggestions for improving medical service quality [7-8]. At present, such research is still in its infancy. Existing studies mostly focus on the analysis of online reviews of a specialist doctor, department, emergency center, or specialized hospital, while there are few studies on large comprehensive top medical institutions [9-10]. At the same time, in the medical and health service industry, due to factors such as the professionalism of medicine, the complexity of diseases, the diversity of scenarios, the personalization of diagnosis and treatment measures, the asymmetry of doctor-patient information, and the uneven quality of information on social media itself, hospital managers generally have not paid attention to exploring valuable information from patients' reviews on social media to guide management practices [11], which may be a pity.

China's health administrative departments have always attached great importance to the medical service level of medical institutions and have been committed to improving the medical services of medical institutions for many years to provide high-quality medical services to the public [12]. In China's medical and health system, tertiary general hospitals are the backbone with the strongest strength. They receive a large number of patients, undertake the function of treating difficult and complicated diseases and critically ill patients, and best reflect the development level of domestic medical institutions and even the development of domestic medical and health undertakings [13].Patients' perceived medical service is a subjective evaluation of the overall level of medical service based on their own experience, expectations, and feelings during the process of receiving medical services. It covers multiple dimensions and is of great significance for improving medical service work [14].

The purpose of this study is to take 7 top large comprehensive tertiary hospitals in four developed cities in China, as the research objects, collect the medical experience review information publicly posted online by patients of these hospitals, use data mining-related technologies to conduct content mining and analysis, understand patients' perceived medical service situation, including the content and focus of attention, key themes, emotional experience, and changes over time, explore the characteristics and laws of patients' online reviews in large medical institutions, and provide methods and references for medical institutions, especially large ones, to mine and utilize patients' online review information and improve medical services.

***Methods***

**Research Subjects**

This study selected 7 large tertiary general hospitals in four cities: Beijing, Shanghai, Wuhan, and Chengdu. Beijing is China's capital and political and cultural center, Shanghai is the most economically developed city in China, and Chengdu and Wuhan are also important cities in China and play important roles in their respective regions [15]. These cities are representatives of cities with dense health resources and high levels of health development and management in China, and also gather some of the best hospitals in China [15]. This study selected 7 hospitals from these four cities. These 7 hospitals have long been ranked among the top 10 in various domestic best hospital rankings, are recognized as top domestic hospitals, and can reflect the highest level of medical services in domestic hospitals [16]. Another consideration for selecting these hospitals is that they serve a large number of patients, so the number of online reviews may be relatively large, which can facilitate the research.

**Data Sources**

A certain review website is one of the earliest established and leading third-party consumer review websites in China [17]. The website requires users to evaluate rationally, not to arbitrarily belittle or personally attack, and not to expose users' private information. This paper selects the content of patients' reviews related to the above 7 hospitals on this review website, collects and sorts out all patients' online review data from 2006 to 2025, as the data source for subsequent mining and analysis. In terms of inclusion and exclusion criteria, hospitals with fewer than 300 online reviews were excluded. It is generally believed that too few reviews are insufficient to reflect the situation of medical institutions. In terms of ethical considerations, these reviews are public and anonymously published content from social media networks, which do not involve privacy and ethical issues. In terms of content crawling methods, Python code was written to automatically crawl the text content of patients' online reviews of the above hospitals.

**Data Processing and Analysis Methods**

***Data Preprocessing***

Since patients' reviews on the Internet are spontaneously written by individuals, the text has no fixed format, the language is relatively arbitrary, and often mixed with network terms, colloquialisms, dialects, etc. Therefore, generally speaking, the vocabulary is relatively rich, and different users have differences in expression habits. Using the Chinese text analysis software ROST CM 6.0, word segmentation and word frequency analysis were performed on the text content of patients' reviews. Then, according to the analysis results, words unrelated to this study were added to the filter word list, words that could not be correctly segmented were added to the custom word list, and finally, words with similar Chinese meanings in the text were classified and merged.

***High-frequency Word Analysis***

High-frequency word analysis is a basic analysis method in text mining, which aims to reveal the core themes, emotional tendencies, cultural characteristics, or language laws of the text by counting the words that appear frequently in the text. Its core logic is: words that appear frequently are often closely related to the core content of the text. By extracting and analyzing these words, key information can be quickly grasped, providing a basis for further qualitative or quantitative research [18].

***LDA Topic Analysis***

Latent Dirichlet Allocation (LDA) is an unsupervised probabilistic generative model used to automatically mine potential topics from large-scale text corpora. Through statistical learning, LDA can infer the distribution of topics in the text and the distribution of high-frequency words under each topic, thereby realizing automatic clustering and extraction of text topics [19].

***Semantic Network Analysis***

Semantic network is a classic social network analysis method, which can construct a network model to reveal the internal connections by analyzing the co-occurrence relationship between elements such as words and concepts in the text. Semantic network analysis breaks through the limitations of traditional word frequency or topic analysis, focusing more on the "relationship" between concepts rather than isolated concepts themselves, and is widely used in knowledge graph construction, text semantic understanding, cross-domain knowledge fusion and other fields [20].

***Sentiment Analysis***

It is an important branch of natural language processing, aiming to automatically identify and extract subjective emotional tendencies contained in the text through algorithms, such as positive emotions, negative emotions, neutral emotions, etc. Its core is to infer the author's or speaker's attitude, opinion, or emotional state by analyzing the characteristics of words, sentence patterns, and context in the text [21].

*Trend Analysis:* The time span of the data collected in this study is relatively large. To further understand the hotspots of attention and emotional tendencies presented in patients' review content at different times and their changing trends over time, this study further subdivides the time range from 2006 to 2025 into four time periods: 2006-2012, 2013-2016, 2017-2020, and 2021-2025, and examines the presentation of patients' attention hotspots and emotional tendencies in these four time periods respectively. Considering that mobile phones and social media applications were not widely used in the early stage, online reviews may be relatively few, so the scope of the first time period is slightly larger, and the remaining time periods are 4-5 years.

*Software and Tools:* The text analysis software ROST CM 6.0 and its enhanced version of the sentiment tendency analysis package tool ROST EA software are Chinese and English text mining and analysis software, which are currently widely used in sociology and management-related research fields [22]. This study uses this software combined with Python programming to conduct data analysis according to the above data analysis methods. Figure 1 shows the overall framework of this study.

**Figure 1.** Overall Research Framework

***Results***

**Included Research Objects**

According to the object selection criteria, Table 1 shows the information of the top hospitals included in the study.

**Table 1.** Included Hospitals

| Serial Number | Hospital | City | Grade of hospital |
|---|---|---|---|
| 1 | XH Hospital | Beijing | Tertiary General |
| 2 | JFJ Hospital | Beijing | Tertiary General |
| 3 | RJ Hospital | | Tertiary General |
| 4 | ZS Hospital | Shanghai | Tertiary General |
| 5 | HS Hospital | Shanghai | Tertiary General |
| 6 | TJ Hospital | Wuhan | Tertiary General |
| 7 | HX Hospital | Chengdu | Tertiary General |
| Total: 7 hospitals in 4 cities, all are large tertiary general hospitals | | | |

**Review Information Data**

Through data crawling, a total of 10,800 pieces of patients' review data of the above 7 hospitals on a well-known domestic online review website were obtained. The time span is from November 2006 to the end of February 2025. The number of words in each review ranges from dozens to hundreds or even thousands, all expressed in Chinese.

**Data Processing and Analysis**

***Data Preprocessing***

In accordance with the processing principles in the method section, synonyms in the text were merged, for example, "□□ (doctor)" and "□□ (doctor)" were unified as "□□ (doctor)", and "□□ (inquire)", "□□ (consult)", "□□ (inquire)" were unified as "□□ (consult)", etc. High-frequency words with no actual meaning, such as "□□ (hospital)", were excluded. The text was processed according to this principle, and then the processed text was subjected to word segmentation and word frequency analysis again, and single characters were excluded. The above processing process was repeated iteratively until the data quality met the data analysis requirements of this study.

***High-frequency Word Analysis***

Word frequency can reflect popularity and importance to some extent, directly reflecting the service focus of patients who posted online reviews. According to the word frequency table generated by ROST CM 6.0 software, the top 300 high-frequency keywords were selected, among which the highest word frequency was "□□ (doctor)" and the lowest was "□□ (medical guide)". Due to space limitations, some high-frequency words are shown in Table 2.

**Table 2.** Top 20 High-frequency Words in Patients' Online Reviews

| High-frequency Word | Word Frequency | High-frequency Word | Word Frequency | High-frequency Word | Word Frequency | High-frequency Word | Word Frequency |
|---|---|---|---|---|---|---|---|
| Doctor | 12275 | Nurse | 2656 | Hospitalization | 885 | Consulting Room | 615 |
| Registration | 5979 | Examination | 2636 | Treatment | 792 | Ointment | 599 |
| Queue | 3899 | Service | 1990 | Effect | 704 | Payment | 577 |
| Appointment | 3498 | Problem | 1374 | Expert Number | 652 | Medical Skills | 479 |
| Outpatient Service | 3246 | Operation | 1366 | Ward | 616 | Charge | 439 |

***LDA Topic Analysis***

The LDA topic model was used to view the implicit topics and semantic content in patients' medical reviews. In the evaluation model, a topic model with a certain number of topics was determined. The lower the perplexity of this topic model in the review corpus, the better the expressive ability of the topic model under this number of topics. After repeated experiments, the optimal number of topics K=5 was determined, with a consistency score of 0.3734 and a perplexity of -6.0465. The following table is the topic-word matrix for mining medical review topics.

**Table 3.** Topic-word Matrix for Mining Patients' Online Review Topics

| Topic 1 (8.88%) | Topic 2 (40.54%) | Topic 3□24.28%□ | Topic 4□7.28%□ | Topic 5□19.02%□ |
|---|---|---|---|---|
| Attitude□0.1379□ | Registration□0.067 | Outpatient | Effect□0.0697□ | Patient□0.0562□ |

| | | | | |
|---|---|---|---|---|
| | 8□ | Service□0.0535□ | | |
| Nurse□0.1193□ | Seeing a Doctor□0.0570□ | Expert□0.0528□ | Medical Insurance□0.0571□ | Doctor□0.0391□ |
| Emergency□0.0563□ | Queue□0.0431□ | Appointment□0.0477□ | Treatment□0.0516□ | Operation□0.0283□ |
| Service Attitude□0.0314□ | Examination□0.0253□ | Convenience□0.0407□ | Friend□0.0440□ | Hospitalization□0.0257□ |
| Method□0.0274□ | Time□0.0246□ | Ordinary□0.0305□ | Have Seen□0.0381□ | Facility□0.0226□ |
| Parking Lot□0.0268□ | Hour□0.0215□ | Environment□0.0289□ | Not Bad□0.0318□ | Medical□0.0214□ |
| Others□0.0254□ | Afternoon□0.0158□ | Service□0.0274□ | Allergy□0.0283□ | Every Time□0.0209□ |
| Clear□0.0210□ | Self-service□0.0157□ | Patient□0.0262□ | WeChat□0.0274□ | Hope□0.0200□ |
| Basically□0.0196□ | Inside□0.0123□ | Generally□0.0232□ | Serious□0.0274□ | Level□0.0183□ |
| Security Guard□0.0190□ | Come Out□0.0119□ | Online□0.0193□ | Tell□0.0255□ | Every Day□0.0155□ |

In the table, the top ten words under each topic are listed according to the probability value, which probabilistically represents the implicit semantic content of patients under a certain topic. From the word probability distribution in the above table, it can be inferred that Topic 1 may be related to outpatient and emergency services, especially mentioning the attitude of nurses and emergency staff, as well as medical peripheral services such as parking and security; the key words in Topic 2 revolve around the experience of the treatment process, involving the waiting time for medical links such as registration, and may also express appreciation for the hospital's self-service mode. From the word distribution of Topic 3, this topic may be reviews related to the experience of outpatient expert appointment services. As a scarce resource, expert registrations are often difficult to obtain. Offline registration is time-consuming and laborious, and may not be successful, but the online appointment model has greatly improved the efficiency of registration and facilitated patients; from Topic 4, it can be inferred that patients may be evaluating the treatment effect, and also mention medical insurance, indicating that medical insurance is also a concern of many patients, expressing the mentality of both wanting to get good treatment and paying attention to the cost burden; from the key words of Topic 5, it may be related to hospitalization, surgery, and ward environment and facilities, expressing concern about technical level and attention to environmental facilities.

***Semantic Network Analysis***

Using the semantic network and social network generation tools of the above ROST CM 6.0 software, a visual network between high-frequency words in the co-word matrix was constructed, and the high-frequency word co-occurrence network was formed through the NetDraw function of the software, so that the co-occurrence relationship between high-frequency words can be observed more intuitively, as shown in Figure 2. Each node in Figure 2 is a high-frequency word obtained in the sample processing. The line between nodes indicates the relationship between the two. The larger the node, the greater the role of the node in the co-occurrence network. The thicker the line between nodes, the stronger the relationship between the two points.

**Figure 2.** High-frequency Word Co-occurrence Network

(English equivalents of some Chinese words in above figure□□□-doctor, □□-registration, □□-attitude□□□-out patient service□□□-appointment□□□-time□□□-queue□□□-nurse□□□-hour□□□-minute□□□-examination□□□-convenience□□□-expert□□□-service□□□-self-service□□□-machine□□□-counter□□□-problem□□□-emergency□□□-environment□□□-in advance□□□-online□□□-patience)

Using the NetDraw function of ROST CM 6.0 software, Betweenness *(describing the decisive role of a specific node in the entire network; nodes with a large role can be called bridge nodes)* was selected to assign values to each node. The larger the value, the larger the node. It can be seen from Figure 2 that the nodes with higher values include core high-frequency words such as doctor, registration, appointment, attitude, outpatient service, nurse, and time. Nodes with higher Indegree (*i.e., in-degree, reflecting the frequency of a node being concerned or cited, describing the influence of a specific node*) include doctor, registration, attitude, nurse, minute, appointment, convenience, expert, service, outpatient service, examination, etc., indicating that patients pay high attention to the service attitude of medical staff and the convenience of medical treatment; nodes with the highest Outdegree (*i.e., out-degree, reflecting the active association ability or radiation range of a node, describing the number of interaction relationships between a specific node and other nodes*) are doctor, queue, registration, appointment, outpatient service, time, hour, examination, nurse, attitude, etc., indicating that doctor service, waiting time, registration convenience, appointment mode, nurse service, and staff attitude are the most direct factors and manifestations affecting patients' perceived evaluation of medical services provided by medical institutions, and "doctor" is in the "core" position in the process of patients' medical treatment.

***Sentiment Analysis***

The sentiment analysis function of ROST EA software divides sentiment types into three levels: positive emotions, neutral emotions, and negative emotions, and each level is subdivided into three emotional intensities: general, moderate, and high. The sorted medical experience review texts were imported into the software, and the sentiment analysis results are shown in Table 4.

**Table 4.** Sentiment Analysis of Patients' Perceived Medical Services

| Sentiment Type | Total (%) | Emotional Intensity | proportion□%□ |
|---|---|---|---|
| Positive Emotions | 46.98% | General□5-15□ | 13.59 |
| | | Moderate□15-25□ | 10.37 |
| | | High□>25□ | **23.03** |
| Neutral Emotions | 0.23 | | |
| Negative Emotions | 52.79% | General□-15-5□ | 11.98 |
| | | Moderate□-25-15□ | 9.21 |
| | | High□<-25□ | **16.44** |

It can be seen from Table 4 that the overall emotional experience of patients' perceived medical services is approximately half positive and half negative, with negative emotions slightly higher than positive ones. Among them, high-intensity positive emotions account for 23.03%, indicating that patients' overall evaluation of the medical services of these top hospitals is positive, which is basically consistent with the reputation of these top hospitals in the industry. Through the specific analysis of the corresponding text data content, it is found that the positive emotions perceived by patients are mainly reflected in appointment registration, self-service machine services, professionalism, environment, and hardware facilities. Negative emotions account for 52.79%, but high-intensity negative emotions only account for 16.44%, and general and moderate negative emotions account for 21.19%. Negative emotions are mainly reflected in service attitude, waiting time, language communication, and complicated processes, indicating that these hospitals still have room for improvement in these aspects. Among all three different sentiment types, neutral emotions account for the lowest proportion, only 0.23%.

***Trend Analysis***

The time was divided into four stages: 2006-2012, 2013-2016, 2017-2020, and 2021-end of February 2025. Due to the relatively small amount of data in the early stage, the time range was appropriately expanded to 2006-2012. Taking the above 7 hospitals as a whole, using the methods introduced in the data processing and analysis section, the hot content and emotional tendencies of patients' attention in each time stage were analyzed respectively. The emotional tendencies were plotted as a line graph in the form of point values, and the hotspots of attention were listed directly on the graph. The specific results are shown in Figure 3. It is interesting to find that in terms of hotspots of attention, the hot content that patients pay attention to is significantly different before 2016 (the first two time periods) and after 2017 (the last two time periods); in terms of emotional tendencies, the proportion of positive emotions shows an overall upward trend, and negative emotions show an overall downward trend. In the same period, the proportion of positive emotions is lower than that of negative emotions. In the third time period(2017-2020), the proportion of positive emotions reaches the highest value, and negative emotions reach the lowest value, which is also the period when the two are closest. After that, positive emotions gradually decline and negative emotions rise somewhat. Overall, with the third time period (2017-2020) as the boundary, it shows a similar "scissors-type" trend.

**Figure 3.** Changes in Patients' Attention Hotspots and Emotional Tendencies in Different Time Periods

## *Discussion*

### Main Findings

The analysis of the top 20 high-frequency words found that patients' attention is more focused on doctors, and their attention to nurses is significantly less than that to doctors. The efficiency of the medical process has a great impact on the medical experience. The medical examination and laboratory links are also likely to directly affect patients' medical experience. The number of mentions of outpatient services is significantly higher than that of inpatient services. Although treatment effect is usually considered the core content of medical services, in terms of medical experience, attention to this aspect is not very high.

LDA topic analysis found that key topics include outpatient and emergency service attitude, medical process, expert appointment, treatment effect, hospitalization and surgery, facility environment, etc. Further observation and analysis of the content in the topic-word matrix table show that patients who posted medical reviews have a mixed attitude towards medical treatment on the whole: On the one hand, they affirm the medical experience from aspects such as appointment and self-service; on the other hand, there are some deficiencies in certain aspects of the medical services provided by the hospital, such as service attitude and long waiting time, which require hospital managers to pay attention to and solve.

Semantic network analysis found that in the semantic network graph, with "doctor" as the core, it diverges to the surrounding. Attitude, registration, service, patience, and convenience are the words with the strongest correlation with it, which indicates that non-technical factors are important factors affecting the medical experience.

Sentiment analysis found that overall, negative emotions account for the highest proportion, followed by positive emotions, with positive emotions slightly lower than negative emotions, and neutral emotions accounting for the lowest proportion, less than 1%.

Trend analysis found that in terms of high-frequency words, in the early stage (2006-2012), patients paid more attention to registration, efficiency, attitude, experts, etc. With the improvement of domestic hospital management and informatization (2013-2016), appointment for treatment and appointment for examination models were gradually promoted, and the appointment system gradually became a hot spot of patients' attention. Around 2019 (2017-2020), the informatization level of hospitals was further improved, and the occurrence of the epidemic also prompted hospitals to vigorously develop online appointment and online service modes; it is also considered that due to the epidemic, patients themselves paid more attention to the hygiene of the hospital; at the same time, with the improvement of hardware construction in major hospitals, more comfortable medical environments could be provided for patients. In recent years (2021-2025), patients' concerns are basically the same as those in the previous time period, but the order has changed, with more attention to hospital hygiene and medical technology. A common situation in large domestic hospitals is that there are many patients, especially in top hospitals, which reflects people's recognition of high-quality medical resources. Therefore, "many people" has been a high-frequency word in the past decade. In recent years, the word "afraid" has appeared frequently. The analysis of its reasons may be related to the epidemic and the fact that patients pay more attention to their own feelings, which also suggests that medical institutions should pay more attention to the psychological emotions of patients. In terms of emotional tendencies, in the time period of 2006-2012, when hospitals were still in the extensive development stage and the informatization level was relatively backward, the proportion of positive emotions was relatively low, far lower than that of negative emotions; then, in the time period of 2013-2016, the proportion of positive emotions increased slightly, and the proportion of negative emotions decreased, which is considered to be related to the continuous improvement of domestic hospital management and construction levels; in the time period of 2017-2020, the government introduced a number of measures to improve medical services, hospital management and construction continued to develop, and the epidemic occurred, making the medical industry widely understood and praised by the public. Under the combined effect of positive factors, the proportion of positive emotions reached the peak of 49.08% in recent years, almost equal to the proportion of negative emotions; in the time period of 2021-2025, although hospitals are still developing continuously, considering the reduction of comprehensive positive factors, the proportion of positive emotions has decreased again, returning to a level basically the same as before the epidemic. However, overall, positive emotions show an upward trend and negative emotions show a downward trend, so the achievements made in the development and construction of top hospitals should be affirmed. It should be noted that it is common for large hospitals in China to have a large number of patients, especially top hospitals, so it is inevitable that service attitudes may not keep up, which may be an important reason for the low proportion of positive emotions. A direct suggestion is that as managers of top hospitals, in addition to focusing on technical level and service quality, they also need to consider more non-medical technical factors such as medical processes and service attitudes.

### Comparison to Previous Work

In recent years, such research has gradually attracted the attention of researchers. In terms of research purposes, one type of research focuses on online review content to improve services [23,24], and another type focuses on the consistency between patients' online evaluation content and the evaluation results of existing other evaluation systems [25,26]. The purpose of this study can be classified into the former.

In terms of research objects, there are many studies on the public's online reviews of a specialist doctor, such as plastic surgeons and orthopedic surgeons [27,28]. There are also studies on online reviews of a department, such as the emergency department and orthopedics [29,30]. Researchers of these two types of studies are often medical professionals themselves, because they pay attention to the fact that online review content will affect the public's choice of a doctor or a department, so they carry out relevant research and publish it in medical professional journals. Another type involves research on hospital online reviews, which can be included in the category of management or information management [31,32]. Our study can be classified into this category.

In terms of research methods, there is also diversity. Qualitative analysis and quantitative analysis are commonly used methods, including manual labeling, Grounded Theory, correlation analysis, regression analysis, etc. [33,34]. Some studies use data analysis, data mining, and artificial intelligence research methods for analyzing review content, such as LDA topic analysis and sentiment analysis [35,36]. This study comprehensively uses a variety of data mining and statistical research methods, aiming to mine the information contained in the data more deeply. In this study, due to the large sample size, data mining and analysis methods were used instead of Grounded Theory or manual labeling to improve efficiency.

In terms of research content, most studies focus on reviews, ratings, and scores[37]. This study mainly focuses on the review content itself and does not involve scores or ratings. A few studies directly focus on relevant negative content, such as complaints and criticisms, and only analyze this part of the content [38], with obvious "problem-oriented" characteristics. In terms of time development, most studies do not pay attention to the changing trends and characteristics of the research content over time, while this study sorts out the changes in high-frequency words and emotional tendencies in nearly 20 years of review content, aiming to study and analyze the changing laws of patients' online reviews from a broader time perspective rather than a single time period.

In terms of research conclusions, most studies show that positive evaluations are in the majority [39], which is somewhat different from the conclusions of this study, which may be related to different research objects and different culture and social background. In many studies, patients' concerns include service attitude, communication, professionalism, medical results, etc., which are basically consistent with this study. Some researchers emphasize that most online evaluation content has little to do with actual medical quality and technical level, but more with some "non-technical" "experiential" factors [40], such as communication and attitude, which is very similar to the findings of this study. Analyzing the reasons for the high proportion of negative emotions, we believe that as top domestic hospitals, these hospitals are undoubted in terms of medical technology and quality, but due to being busy with work, there may be deficiencies in services. This study also found that positive and negative emotions constitute the main body of emotional tendencies, and neutral emotions account for an extremely low proportion, which is almost negligible. This is consistent with Merchant's [41] view that users tend to show an obvious emotional tendency, positive or negative, when posting reviews online.

**Strengths and Limitations**

We acknowledge that there are some limitations in our study. First, the study only selected 7 top large tertiary general medical institutions in China as the research objects. Future research can consider expanding the research scope, including more medical institutions of different types and grades, and including more online review content for mining and analysis, so as to compare the differences between different institutions. In addition, although sentiment analysis was conducted on the overall text content, sentiment analysis was not further conducted on each key topic. Future research can refine this work.

Our study also has some strengths. *First, we s*elected some representative top hospitals in China as research objects, which has not been seen in other studies. These hospitals have a large number of patients and high social attention, so this selection reflects the attention to the issue of patients' online reviews from the perspective of public health services and hospital management. Additionally, the study includes a large sample size, a long-time span, comprehensive analysis content, and adds the analysis of changing trends over time, making the research results more abundant. At last, the methods used are relatively advanced, reducing the inefficiency of manual analysis, and are suitable for large amounts of data.

**Conclusions**

This study analyzed the medical review content posted by patients on social media related to some top hospitals in China. The results show that the content that patients focus on includes: registration, queuing, examination, service, surgery, effect, cost, etc. These contents can be divided into five key themes: service, process, appointment, effect, and environmental facilities, and are associated with "doctor" as the core. The overall emotional tendency is approximately half positive and half negative, with positive emotions slightly lower than negative ones. The changing trend of patients' main concerns over time is that the attention to registration, queuing, and attitude gradually decreases, while the attention to environment, technology, and self-psychology gradually increases; the changing trend of emotional tendencies over time is that positive emotions first gradually increase and then decrease, and negative emotions first decrease and then increase, indicating that emotional tendencies may be affected by various internal and external factors, but overall, positive emotions show an upward trend and negative emotions show a downward trend. Managers of top hospitals should pay more attention to "non-technical" service factors.

**Acknowledgments**

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**Conflicts of Interest**

None declared

**Data Availability**

Online review contents are publicly accessible. Researchers interested in this study and able to provide scientific and reasonable suggestions should contact the corresponding author (X L) for cooperation. Relevant analysis codes will be provided upon request for reproducibility purposes.

**Author Contributions**

Xiaolei Liu: Research design, data analysis, paper writing
Li Zhao: Data collection, data analysis, paper writing
Wei Liu: Data collection, data verification, paper writing
Danyang Hu: Software tool use, program writing and debugging
Min Chen: Research design, determination of data analysis methods, final review of the paper

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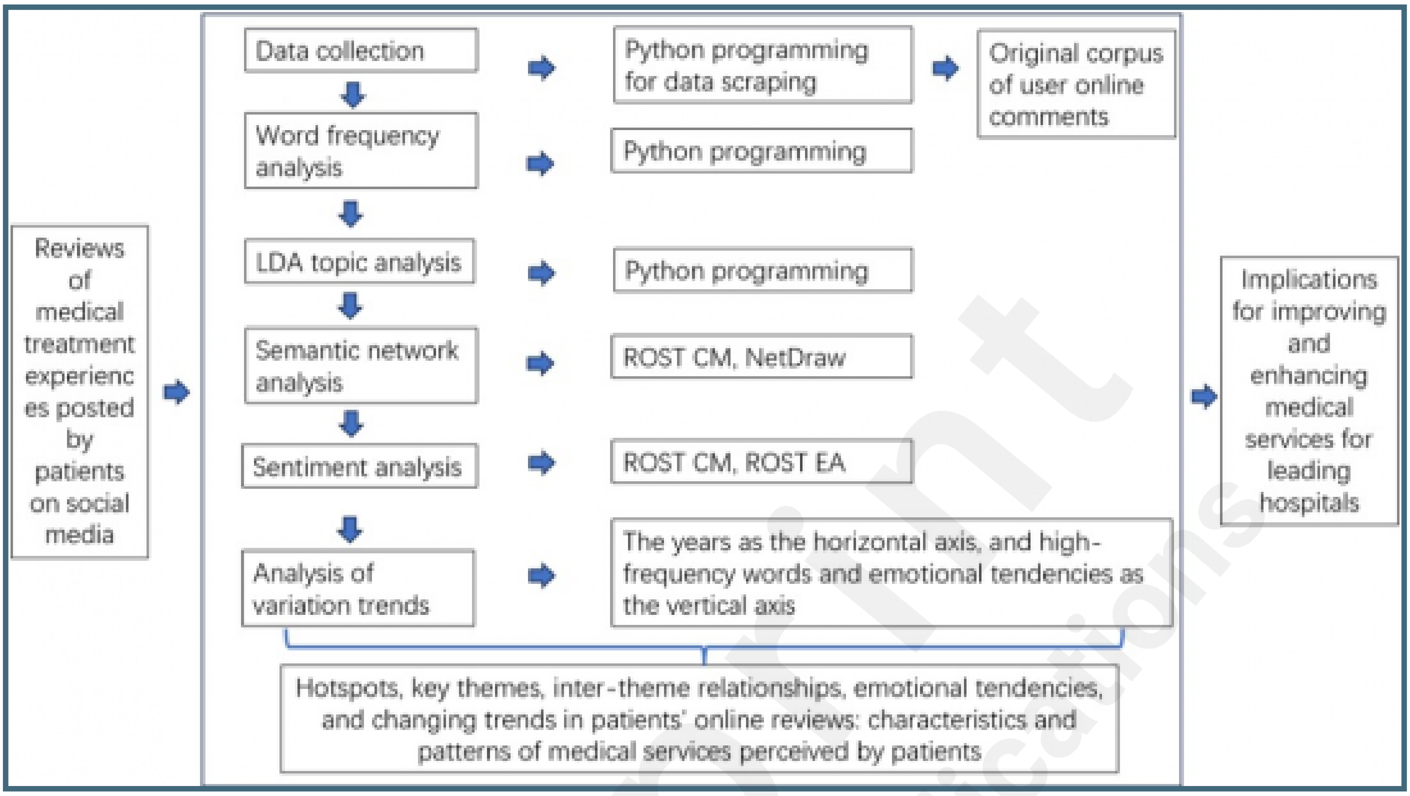
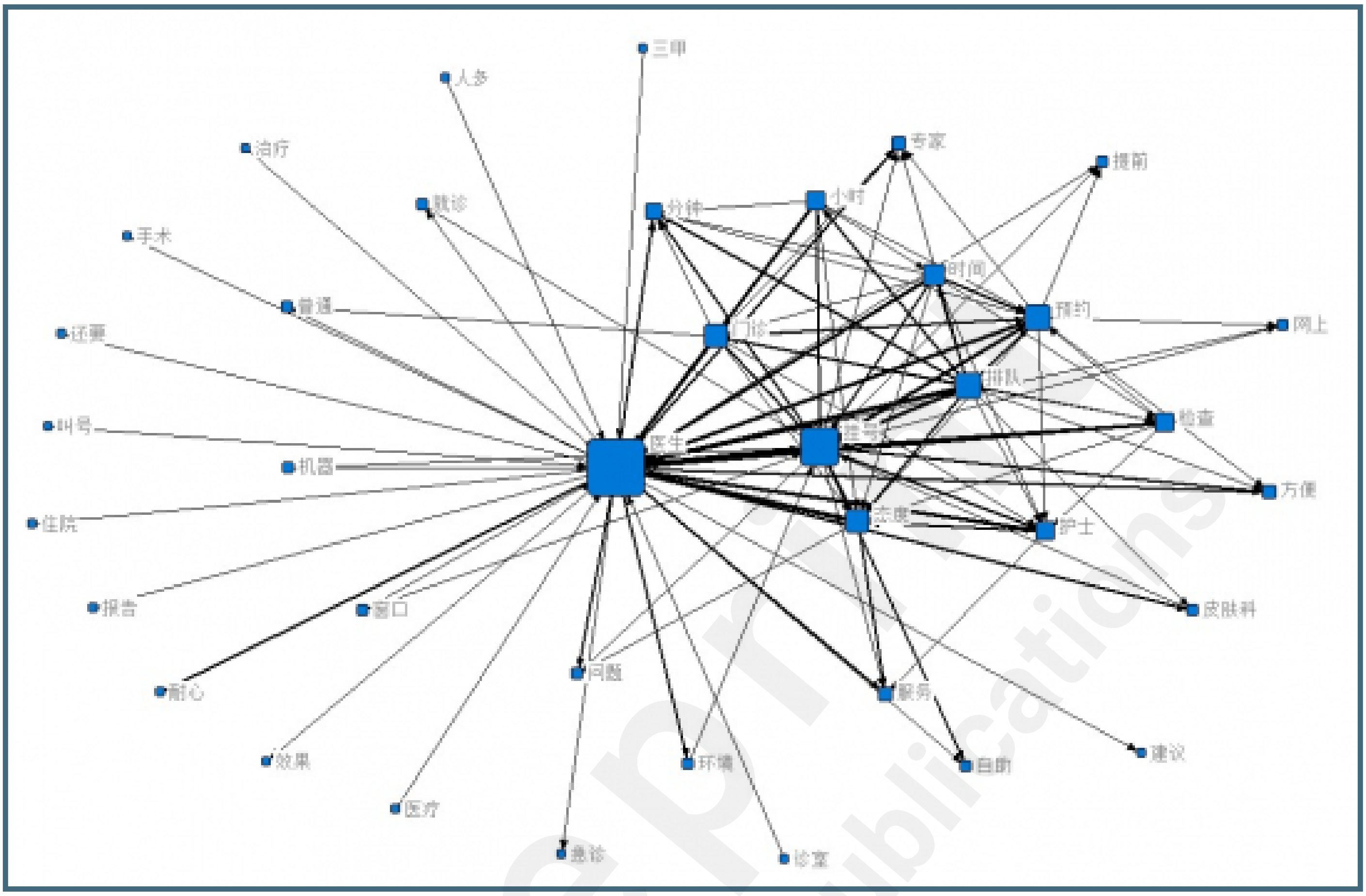
# Supplementary Files

# Figures

Overall Research Framework.



High-frequency Word Co-occurrence Network.



Changes in Patients' Attention Hotspots and Emotional Tendencies in Different Time Periods.