Evaluating Hospitals Quality Based on the User Reviews on the Internet

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Abstract:

This study aimed to explore the current public evaluation status of general hospitals in China, and to provide suggestions for future directions of general hospitals by comparing the differences in public online rating and evaluation data. The general hospital rankings were obtained based on the General Hospital Ranking List released in 2018 by the Hospital Management Institute of Shanghai's Fudan University. After determining several dimensions of data collection, the Python Web Crawler Technology was applied to obtain the assignment scores and user reviews of the Chinese general hospitals on Dianping platform. Besides, the relationships among various factors of Chinese general hospitals were analyzed from the patient perspective. The findings show that patients held negative emotional value towards hospital evaluation. The paper developed guidelines to facilitate patients and family members to use others' medical experiences as a reference to help them select a suitable hospital.

Keywords: *Decision analysis, Hospital evaluation, Data mining, Sentiment analysis, Online review*

1. Introduction

With the rapid development of the Internet and the World-Wide Web, the open framework concept of "user-oriented and user participation" is advocated, and Internet users no longer passively receive the Internet information (Snyder *et al*., 2011). Instead, they begin to develop from "pay attention to information" to "share information". The Internet has changed the lifestyles of people, which has become an indispensable part of their daily life (Chekwa & Daniel, 2014). For instance, some people make comments on some events, people, and commodities by virtue of platforms such as Microblog, Blog, forum, and such comment information expresses various emotions of the public on a particular event, including happiness, anger, sadness, joy, support and objection. Thus, analyzing such reviews helps the institution or individuals to make a decision.

With the increase in hospital commercialization degree, more and more local hospitals are available, and the competitions between hospitals become increasingly fierce (Brekke, Siciliani, & Straume, 2011; Herr, 2010). Consequently, a hospital should understand its weaknesses and strengths of the similar hospital, and thereby take improvement measures to prevail over the related hospitals. With the accelerating development of medical informatization, numerous third-party online review platforms, such as Dianping and Aibang, support users to make comments on their medical experience (Chen & Zheng, 2020; Lee, 2017). At the same time, multiple patients or family members are willing to actively share their feelings on hospital treatment efficacy and medical staff service attitude. For other patients or family members, they can use others' medical experience as a reference, which helps them select a suitable hospital. Mining of the review information mainly focuses on the e-commerce field, while research on online hospital review lacks so far. As a result, it is an extremely significant research project to use the abundant review resources to accurately mine the user focus features and sentiment orientation on hospitals, and to compare the corresponding elements of similar hospitals according to patient sentiment orientation, thus providing decision-making support for patients.

2. Literature Review

The existing studies on medical evaluation mainly focus on hospital evaluation, online medical information sharing, and online review characteristics, as well as sentiment analysis.

2.1 Patient Satisfaction Research

Currently, the patient satisfaction is mainly measured and assessed utilizing a questionnaire, and the popular patient satisfaction scales are mainly modified based on the Patient Satisfaction Instrument (PSI) scale (Hinshaw & Atwood, 1982) and Patient Satisfaction Questionnaire (PSQ) (Wilkin *et al*., 1992). The PSQ evaluates medical service through 8 dimensions. Patient satisfaction belongs to the customer satisfaction category; therefore, some scholars introduce the customer satisfaction scale into the medical service field to evaluate patient satisfaction from 5 aspects, namely reliability, responsiveness, tangibility, empathy, and assurance (Parasuraman *et al.*, 1988). Naidu (2009) had drawn similar conclusions, and he classified patient satisfaction into five dimensions: healthcare result, service accessibility, nursing, doctor-patient communication, and empathy (device advancement and hospital cleanliness). Scholars use inconsistent measuring indexes of patient satisfaction. Still, all of these scales reflect the overall patient satisfaction on medical service, their effectiveness is also verified in the experiment, and they can provide suggestions for improving patient satisfaction. Sprague and Holschuh (2019) investigated the average satisfaction of cancer survivors and statistically significant differences through telephone. Magrey *et al.* (2019) collected relevant demographic statistics to carry out a network-based cross-sectional study on disease features of 2,755 patients. Their results suggested that, a majority of patients expressed overall satisfaction on symptom improvement rate, administration frequency, administration method, usability, patient support service, and side effects.

2.2 Patient Choice of Hospital

Scholars have conducted extensive research and exploration on the selection of medical institutions. For instance, Koch-Weser *et al.* (2019) carried out experiments on the preference of hospital type among the Internet members constituted by 1,005 Massachusetts residents in 2016. Their results suggested that, patients preferentially considered quality rather than costs as the perceived risk increased. Abraham *et al.* (2011)conducted a questionnaire survey on 467 patients in Minnesota, and their results indicated that, the word-of-mouth of the medical institution was the primary factor affecting patient choice. At the same time, the convenience also had certain influence. Wun *et al.* (2010) discovered that concerning doctor selection, convenience and friend recommendations were the most important factors affecting the first choice of hospital among patients. At the same time, doctor medical skills and price also affected the repeated selection behavior of patients. Chauhan *et al.* (2019) evaluated data collected from 258 patients from both public and private hospitals in two Indian states through empirical analysis. Their research revealed that, treatment quality, cleanness, hospital reputation and amenities (such as payment and food facilities) were the important factors affecting a patient choice of a hospital. Therefore, scholars begin to research the patient choice of hospital in the medical community in the presence of network information. When examining the influence of price on the patient choice of a hospital through telephone counseling, it is found that price and the perceived quality have a significant influence on patient purchasing behavior (Liu & Ye, 2015).Aggarwal *et al.* (2018)conducted semi-structured interviews on the purposeful samples of 25 males. Among them, 14 men selected to receive treatment at the closest cancer centers. The results suggested that, effective hospital-level information was required to guide patient choice.

2.3 Online Medical Information Sharing

The online medical community breaks the spatial and temporal restrictions, closely associates users with users, medical staff, and medical institutions, and provides a stable platform for their communication and cooperation (Van der Eijk *et al.*, 2013). Horrell *et al.* (2019) launched a 5-week Facebook advertisement activity targeting adults aged over 15 years who were interested in lung cancer to increase the participants in the LungCancer.net community. That study proved the feasibility of using Facebook advertisements to promote and develop the online health community. At present, studies regarding online medical community knowledge sharing mostly focus on the knowledge sharing influencing factors (Yan *et al.*, 2016), and user participative behaviors (Xiaoniu & Shizhong, 2016). At the same time, few studies are conducted to explore the opinion expression and emotional analysis on the text contents semantically from the perspective of user knowledge sharing content. Lu *et al.* (2017) analyzed the user questions in MedHelp.org and explored the stakeholders, hot topics, and sentiment orientation in the questions. Some scholars adopt the machine learning method to classify emotions and distinguish corresponding sentiment polarity in the cancer community user posts (Biyani *et al.*, 2013).

2.4 Online Review Features and Sentiment Analysis

At present, research on opinion mining and sentiment analysis can be classified into three levels after years of development, namely documents, sentences, and words (Liu, 2015). According to the definition, user opinion expression includes three aspects, namely, feature, opinion word, and orientation. The aspect level mines the review features and sentiment orientation. From the point of view of aspect level, mining can be divided into explicit (Chinsha & Joseph, 2015), and implicit (Hai *et al.*, 2015) aspects, but research on implicit opinion mining is greatly restricted due to the restrictions of the research field and possible causes (Xia, Wang, Chen, & Zhai, 2016).

In terms of the application method, mining can be classified as sentiment analysis using machine learning methods like support vector machine (SVM) (Poria *et al.*, 2014), semantic analysis using sentiment dictionary (Cambria, 2016), and the deep learning-based and other neural network methods(Du, Gui, & Xu, 2016). From the perspective of the research field, research concentrates on e-Commerce, hotel, film-television, and catering industries. Besides, some scholars have applied mining in the medical industry; for instance, Yang and Jiang (2018) utilized the heterogeneous medical information network to mine the user recommendation information in Other Health Coverage (OHC). It turns out that the proposed method effectively measures the user interests in online discussion.

Thus, it is clear that the medical field has not been explored in related research, namely, opinion mining and sentiment analysis on the user reviews after real medical experiences in the online medical community. No thoroughly annotated text corpus is available in this field. Thus, this paper proposed to mine and analyze relevant reviews based on the feature rule method.

3. Materials and Methods

3.1 Data Sources

The Dianping website, which is set up in 2003, is the leading network platform that integrates local life and transaction information in China, and the earliest constructed independent third-party consumption review network in the world. It provides information services like supply of supplier information, self- and other consumer reviews, and consumption discount. It initiates and leads the third-party review pattern, which has become a new hotspot on the Internet, and users can freely express their reviews on the suppliers and their feelings. Almost all review information is derived from online users, which eventually provides a reference for the mass consumers.

In this study, all data were derived from the Dianping website, and the objects of data collection were the top 10 general hospitals based on the General Hospital Ranking List released by the Hospital Management Institute of Shanghai's Fudan University in 2018, including Peking Union Medical College Hospital, West China Hospital of Sichuan University, Chinese PLA General Hospital (CPLAGH), Rujin Hospital of Medical School of Shanghai Jiaotong University, Zhongshan Hospital Affiliated to Fudan University, First Affiliated Hospital of Sun Yat-Sen University, Xijing Hospital of Air Force Military Medical University, Tongji Medical College Affiliated to Huazhong University of Science and Technology, Huashan Hospital Affiliated to Fudan University, and Peking University First Hospital.

3.2 Research Instruments

Multiple data analysis and mining-related libraries in Python, including Pandas, Numpy, and Matplotlib, were used in research. Of them, Pandas includes plenty of libraries and some standard data models, which provides the tools required to efficiently manipulate large datasets, as well as numerous functions and methods to rapidly and conveniently process data. The Numpy library can give a lot of advanced numerical programming tools, such as the matrix data type, vector processing, and precise operation libraries, which are exclusively used for rigid digital processing. Matplotlib is a 2D-plotting library for Python, which only requires few lines of codes to produce the plots through Matplotlib, such as histogram, bar chart, and scatter diagram, thus more intuitively exhibit the data results. In this study, these data analysis libraries were introduced for score comparison, description, and correlation analysis on the obtained data, thus identifying the drawbacks and proposing corresponding countermeasures.

4. Data Analysis

In this study, the web crawler technique was utilized to crawl all evaluation information on the Dianping website, including hospital name, star-class assessment, per capita cost, hospital score, facility score, registration score, review content, and review content quantity distribution (including positive review, moderate review, and negative review numbers). Some of the obtained hospital evaluation information is shown in Table 1.

Table 1: Hospital evaluation information

	Per-capita	Doctor	Facility	Registration	Positive review	Moderate review	Negative review	Number of reviews	Star
Peking Union Medical College Hospital	818	9.2	9.3	9.1	869	149	144	1162	5
West China Second Hospital of Sichuan University (Jinjiang Hospital)	1984	9.2	9.2	9.1	83	7	7	97	5
Chinese PLA General Hospital	1953	9.1	9.2	9	456	96	141	693	5
Rujin Hospital of Medical School of Shanghai Jiaotong University	531	8.8	9	8.3	975	337	519	1831	3.5
Zhongshan Hospital Affiliated to Fudan University	431	9	9.1	9	479	77	177	733	4
First Affiliated Hospital of Sun Yat-sen University	1559	5.8	6.7	5.9	44	15	33	92	2
Xijing Hospital of Air Force Military Medical University	1165	9.1	8.4	8.6	91	8	9	108	4.5
Tongji Medical College Affiliated to Huazhong University of Science and Technology	1680	9.1	9.1	9	131	32	48	211	4.5
Huashan Hospital Affiliated to Fudan University	307	5.8	5.9	5.5	1131	600	688	2419	2
Peking University First Hospital (Outpatient Department)	661	9.2	9.2	9.2	247	41	53	341	5

4.1 Text Analysis

This study explored the patient evaluation on comprehensive image and sentiment orientation. It carried out high-frequency word statistics and text sentiment analysis on patient reviews from the point of view of user reviews on hospitals. There was a total of 7,684 user reviews on hospitals on the Dianping website. This study also split the keywords on the review contents, words like conjunctions and adverbs in the split words were eliminated.

The key words were sorted according to the word frequency from high to low, and the top 20 high-frequency words were extracted, as shown in Table 2. It was discovered from these high-frequency keywords that, the user concerns were mainly in “hospital”, “doctor”, “registration”, “queue”, and “appointment” aspects. Moreover, words like “attitude”, “sensation”, and “medicine” also occurred at a high frequency.

Table 2:The top 20 high-frequency words

Keyword	Word frequency	Keyword	Word frequency
Hospital	9220	Nurse	1756
Doctor	8560	Examination	1460
Registration	4114	Huashan Hospital	1455
Queue	2982	Expert	1439
Seeing a doctor	2750	Good	1389
No	2363	Dermatology Department	1342
Appointment	2088	Medicine	1274
Patient	2029	Time	1253
Attitude	2000	Sensation	1171
Outpatient	1775	Result	1126

The review statements were classified according to the topic model, and the number of categories was set at five. The following five types of topics and related important words were obtained as shown below:

Topic 1: (hospital service attitude)

Hospital, registration, number, queue, seeing a doctor, patient, attitude, appointment, register

Topic 2: (the process of a patient seeing a doctor)

Doctor, number, queue, seeing a doctor, do, register, attitude, patient, outpatient, appointment, nurse

Topic 3: (communication between doctor and patient)

Queue, seeing a doctor, appointment, attitude, register, outpatient, patient, do

Topic 4: (patient services provided by the nurse)

Registration, queue, seeing a doctor, register, patient, attitude, do, nurse, appointment

Topic 5: (doctor's professional degree)

Doctor, say, number, registration, seeing a doctor, appointment, register, real, outpatient, do.

It was seen from various topics analyzed based on the topic model that patients paid attention to the difficulty in seeing a doctor as well as doctor attitude and a professional degree.

4.2 Correlation Analyses on Various Indexes

In this study, the SnowNLP package was used for sentiment analysis on the Chinese texts. The value (range, 0-1) of SnowNLP sentiment analysis represented the probability that this sentence expressed the positive emotion, and an emotion value closer to 1 showed the more positive emotion. It was discovered after observing the sample review data and the emotional values that most users on the Dianping website had positive reviews on the hospital. However, observation on a small amount of data might lead to conclusion bias. Therefore, to avoid such a phenomenon, this study utilized the mean () function to process the sentiment analysis results. The obtained mean lying in the [0.1,1.3] interval, and such small value demonstrated that the users held a negative attitude to general hospital evaluation. Subsequently, this study calculated the mediums, and the result was <0.1, which suggested that the mediums were not only higher than the means, but also close to 0 (totally negative). Such results indicated that most reviews expressed the dissatisfaction. Thus, these dissatisfied reviews might be used in the future improvement direction of hospital construction. According to the findings, this study sorted out the strengths and weaknesses in the reviews and proposed corresponding countermeasures for the reference of subsequent research.

To grasp the overall data distribution, the data frame described was applied first of all to check the precise distribution of numeric data; then, the comments were divided based on contents and quantity, the numbers of positive, weak and moderate comments were listed independently for the convenience of observation and data analysis. The data were standardized as shown in Table 3.

Table 3:Summary of the standardized data

	Per-capita	Doctor	Facility	Registration	Positive comment	Moderate comment	Negative comment	Number of comments	Mean emotion value	Medium emotion value	Star
0	0.305	1	1	0.973	0.75897	0.2395	0.2012	0.4303	0.50949	0.27	1
1	1	1	0.97	0.973	0.035879	0	0	0.0018	0	0.186	1
2	0.982	0.97	0.97	0.9459	0.379025	0.1501	0.1968	0.2386	0.93993	0.638	1
3	0.134	0.88	0.91	0.7568	0.856486	0.5565	0.7518	0.6942	0.76739	0.219	0.5
4	0.074	0.94	0.94	0.9459	0.400184	0.118	0.2496	0.2353	0.80352	0.348	0.67
5	0.747	0	0.24	0.1081	0	0.0135	0.0382	0	0.57724	0.024	0
6	0.512	0.97	0.74	0.8378	0.043238	0.0017	0.0029	0.0059	0.33424	0	0.83
7	0.819	0.97	0.94	0.9459	0.080037	0.0422	0.0602	0.0485	0.66441	0.114	0.83
8	0	0	0	0	1	1	1	1	0.35456	0.04	0
9	0.211	1	0.97	1	0.186753	0.0573	0.0675	0.094	1	1	1

Subsequently, various indexes were performedusing correlation analysis. Then the correlated variables were analyzed to measure the correlation degree of two variables. Correlation analysis should be performed when there was a certain association or probability between the correlated elements. The results were shown in the following Table 4.

Table 4:Correlation analysis of elements

	Per-capita	Doctor	Facility	Registration	Positive comment	Moderate comment	Negative comment	Number of comments	Mean emotion value	Medium Emotion value	Star
Per capita	1	0.176	0.225	0.2197	-0.68	-0.6	-0.6	-0.661	-0.23	-0.1	0.332
Doctor		1	0.967	0.9889	-0.21	-0.5	-0.4	-0.386	0.196	0.44	0.939
Facility			1	0.9807	-0.22	-0.6	-0.5	-0.416	0.293	0.5	0.906
Registration				1	-0.27	-0.6	-0.5	-0.454	0.234	0.5	0.953
Positive comment					1	0.89	0.89	0.9632	0.101	-0	-0.3
Moderate comment						1	0.98	0.9779	-0.07	-0.2	-0.56
Negative comment							1	0.9729	0.023	-0.2	-0.57
Number of comments								1	0.013	-0.1	-0.47
Mean emotion value									1	0.69	0.123
Medium emotion value										1	0.525
Star											1

It was observed from the table that doctor's evaluation, hospital facility evaluation, and registration difficulty showed strong correlations suggesting the greater difficulty in registering doctors with superior medical skills and hospitals with better facilities. Besides, the final star-class assessment was also related to these three items.

5. Results and Discussion

Overall, this study conducts status survey, evaluation factor correlation analysis and user evaluation sentiment analysis based on the public reviews of the top 10 Chinese general hospitals on the Dianping website. The research results are obtained as follows.

The emotional value on hospital evaluation is negative on the whole: in the evaluation texts, the reviewers mostly hold negative emotion suggesting that the difficulty and expense of medical service remain a long-term social problem. People pay more attention to health as the living standard improves, but healthcare, especially for the medical service cannot satisfy people's demands.

The influencing factors of overall evaluation are quite concentrated. It is seen from the above-mentioned research that the general assessment on a hospital is mainly dependent on the doctor's medical skills, hospital facility, and difficulty in registration (Mosadeghrad, 2013). Such a result indicates that, when a patient selects a hospital for medical treatment, s/he will consider not only the doctor's medical skills, but also the comprehensive services provided by the hospital (Qadri *et al.*, 2012), including the hardware facility level. Moreover, another crucial measuring factor is the difficulty of hospital registration. The more difficult registration denotes that the patient should pay a higher cost for medical treatment, and s/he will select a suitable hospital after careful consideration (Lee & Jones, 1933).

The improvements should pay more attention to patient concerns. We also discover from the evaluation texts that patients pay attention to words, such as "registration", "queue", and "appointment" (Su *et al.*, 2006), suggesting that it is more difficult to see a doctor at a more advanced hospital, and various pathways should be taken to register. Meanwhile, it is observed from words like "expert", "outpatient service", and "attitude" thatpatients pay more attention to the doctor's professional level (expert or not). Furthermore, the doctor's attitude in outpatient service has an essential impact on the patient.

6. Conclusion

This study attempts to analyze the patient review contents based on the online users, and to reveal the patient evaluation on the Chinese general hospitals through topic model analysis, correlation analysis, and sentiment analysis methods. This study shows the objectiveness and orientation of patient evaluation data from the perspective of patient evaluation based on the patient-generated evaluation contents, which serves as a supplement compared with the expert evaluation-oriented hospital evaluation. On the one hand, the evaluation data corroborate the expert evaluation mutually. On the other hand, they can serve as a supplement of user satisfaction. The reader satisfaction survey is performed in previous hospital assessments mainly through a questionnaire survey, but the investigation process and informants are susceptible to subjective factors, making it impossible to achieve the initial goal of satisfaction survey; by contrast, the patient online evaluation data-based survey is more objective.

Additionally, the sentiment analysis of patient reviews also allows to judge the patient use orientation, to reinforce the positive emotion and to control the negative emotion.

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