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Influencing factors and mechanism of doctor consultation volume on online medical consultation platforms based on physician review analysis

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Yan Wan, Ziqing Peng, Yalu Wang, Yifan Zhang and Jinping Gao
School of Economics and Management,
Beijing University of Posts and Telecommunications, Beijing, China, and
Baojun Ma
School of Business and Management, Shanghai International Studies University,
Shanghai, China

Abstract

Purpose – This paper aims to reveal the factors patients consider when choosing a doctor for consultation on an online medical consultation (OMC) platform and how these factors influence doctors' consultation volumes.

Design/methodology/approach – In Study 1, influencing factors reflected as service features were identified by applying a feature extraction method to physician reviews, and the importance of each feature was determined based on word frequencies and the PageRank algorithm. Sentiment analysis was used to analyze patient satisfaction with each service feature. In Study 2, regression models were used to analyze the relationships between the service features obtained from Study 1 and the doctor's consultation volume.

Findings – The study identified 14 service features of patients' concerns and found that patients mostly care about features such as trust, phraseology, overall service experience, word of mouth and personality traits, all of which describe a doctor's soft skills. These service features affect patients' trust in doctors, which, in turn, affects doctors' consultation volumes.

Originality/value – This research is important as it informs doctors about the features they should improve, to increase their consultation volume on OMC platforms. Furthermore, it not only enriches current trust-related research in the field of OMC, which has a certain reference significance for subsequent research on establishing trust in online doctor–patient relationships, but it also provides a reference for research concerning the antecedents of trust in general.

Keywords Online medical consultation (OMC), Doctor consultation volume, Physician review, Physician trust, Doctors' soft skills, Doctors' service feature

Paper type Research paper

1. Introduction

The medical industry has long attracted societal attention both at national and international levels. At the same time, continuous improvements in living standards and attention to health, longer life expectancy, aging population, urbanization and increases in the disease spectrum have fostered demands for medical treatment. This demand is not confined to the treatment of the disease alone; disease prevention has also become a trend. An increasing

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number of people require professional and reliable health guidance. Consequently, current allocation of resources for medical and health care is insufficient to match the growing demand for professional consultation in the pursuit of healthy lives. The imbalance between the supply and demand of medical services is becoming increasingly prominent. Fair and efficient allocation of medical resources is urgently required to meet the growing demand for medical treatment.

In this context, the internet has the advantage of breaching time and space constraints and providing a pioneering way to correct the imbalance of medical resource allocation through online medical consultation (OMC) platforms. In contrast to other countries that use the internet only as a supplementary resource in the medical industry, China is looking to the internet to solve current medical resource shortages. OMC platforms with health consultation as the main business, such as "chunyuyisheng.com" and "dxy.com," have emerged. OMC has been found effective in improving medical resource allocation (Xiong and Zhao, 2017). It presents a new communication tool for doctors and patients. Patients can select a doctor on an OMC platform through a terminal device (e.g. a computer or mobile phone) and consult the doctor about health issues via text, graphics or voice calls. Similarly, doctors can reply to inquiries through the same platform (Chiu, 2016).

OMC presents a new option for people to conduct health management and consultations and has been widely used in recent years. For example, in "chunyuyisheng.com," the average number of health consultations reached 330,000 per day in 2016 [1]. It is evident that OMC in China is growing rapidly. The role of OMC was highlighted during the outbreak of COVID-19, which is considered a global pandemic by the World Health Organization (WHO). People who want to seek medical attention but are afraid of cross-infection turn to OMC platforms. Even when the COVID-19 pandemic subsides, people are likely to continue consulting online for minor, chronic and common diseases for convenience. Hence, OMC has become increasingly necessary, welcomed and popular (Katz and Moyer, 2004; Shuyler and Knight, 2003; Umefjord *et al.*, 2006). Therefore, it is imperative to improve OMC platforms' service quality and user experience to promote its continuous use and to attract new users. Accordingly, the selection behavior of users on OMC platforms and the underlying mechanism should be explored first.

The selection behavior of patients on OMC platforms is different from that in traditional offline medical services. In the latter, people can only obtain health information through medical workers, and the access methods are extremely limited (Carlsson, 2000). In addition, each patient has a unique medical issue; therefore, information asymmetry in the medical field is a serious problem (Li *et al.*, 2016). When people choose a doctor, their choice is influenced by the doctor's hospital, title and years of experience, which lead people to flock toward the most excellent medical resources (e.g. key hospitals and expert physicians), even though they do not necessarily need them, causing some common medical resources to remain idle and under-utilized. This suggests that the main problem at present is not the shortage of medical resources, but their unreasonable allocation (Yu *et al.*, 2016).

With the emergence of online health services and physician review websites, patients can share their opinions about doctors' service attitudes, communication and other aspects of the medical service process. Consequently, patients can make decisions and choose doctors after examining doctor reviews, as well as the personal information that the doctor posts. Physician reviews on OMC platforms provide patients with considerable information, such as doctors' response speed and service attitude. This indicates that the factors considered by patients when choosing doctors online may be different from those considered in offline medical services. Patients no longer have to select their doctors based on limited information, such as professional titles and hospital level (i.e. Grade 3 and first-class hospitals). Therefore, we aim to explore the influencing factors and the mechanisms of doctor consultation volume on OMC platforms through physician reviews.

Although some studies have used algorithms such as latent Dirichlet allocation (LDA) to extract hidden topics from physician reviews on online health communities and physician review websites, at least two research gaps exist in the current literature. First, the topics discussed in these studies are not sufficiently comprehensive and detailed, and they do not consider factors, such as the platform, word of mouth and overall service experience. Second, the existing literature on feature extraction of physician reviews only extracts service features and does not explore the impact of these features on doctors' consultation volumes.

To address these research gaps, we investigate two research problems:

(1) From a technical perspective, how can useful features be extracted from a large volume of physician reviews?

(2) In application, what do patients care about in the OMC process? How do these factors affect doctor consultation volumes?

This study uses a feature extraction method (based on keyword extraction and the PageRank algorithm) to explore the features that patients pay attention to when selecting doctors, as well as patients' attention toward and satisfaction with each feature. We also study the mechanism through which doctor service features affect the consultation volume. In theory, we provide a new method to extract features from physician reviews and identify factors that influence doctor consultation volumes on OMC platforms. The results enrich the research in the field of OMCs. In application, we provide specific suggestions for doctors on OMC platforms to improve service quality, attract more patients and increase consultation volumes. This study also promotes the development of the OMC industry.

2. Literature review

2.1 Physician reviews

The design of reviews on OMC platforms was derived from the field of e-commerce. Online reviews have been verified in theory and practice, an important factor that affects consumer choice in this field (Lee and Youn, 2009; Li and Hitt, 2010). The importance of reviews also applies to the field of OMC. In terms of physician reviews, the quantity (Lu and Wu, 2019), the emotional tendency (Han *et al.*, 2019; Li *et al.*, 2015) and their linguistic structure can affect the reputation, authority (Menon, 2017) and selection rate (i.e. consultation volume) of doctors (Alodadi and Zhou, 2016; Grabner-Krauter and Waiguny, 2015; Li *et al.*, 2019b). In addition, the specific aspects of the OMC process that patients primarily focus on can be derived from physician reviews. Therefore, doctors have the necessary information to improve their service level and consultation volume (Liu *et al.*, 2019). In contrast to e-commerce, online medical services do not provide a refund or return. Hence, patients tend to be more careful in selecting doctors and need more information to help them make decisions. OMC platforms provide several numerical information to reflect the doctor's professional title and speed of response; however, additional details on service, diagnosis and treatment effect still need to be obtained from physician reviews. In addition, most reviews in e-commerce are short and meaningless praise templates, posted for the sake of good reviews. Reviews on OMC platforms, in contrast, are very real, specific and have more reference value. Therefore, we aim to explore the influencing factors and mechanisms of doctor consultation volume on OMC platforms through doctor reviews.

Although some studies have explored the factors that patients pay attention to in the process of consultation through behavioral experiments (Li and Hubner, 2019), qualitative analysis (Asanad *et al.*, 2018; Detz *et al.*, 2013; Lagu *et al.*, 2019; Menon, 2017; Orhurhu *et al.*, 2019; Ryskina *et al.*, 2020), quantitative analysis (Li *et al.*, 2019a) or text mining methods (Hao and Zhang, 2016; Liu *et al.*, 2019), the topics analyzed in these studies are not sufficiently comprehensive. We list some of the factors that have already been discovered or studied in Table 1. Factors such as platform, word of mouth and overall service experience have not been considered. Additionally, these studies merely examined the topics of physician reviews on OMC platforms and did not analyze their effect on doctor consultation volumes.

2.2 Feature extraction

To extract useful, comprehensive and detailed factors from a large volume of physician reviews, we use the feature extraction method. Feature extraction aims to automatically identify product features in reviews (Yan *et al.*, 2015), which can effectively solve the problem of review overload on various online platforms. Scholars have applied various text feature extraction methods.

Based on the method of frequent words, researchers believe that frequent nouns and adjectives reflect genuine features and emotions. Therefore, feature extraction can be implemented based on this idea (Afzaal *et al.*, 2016). The method of association rule mining can express the problem as looking for "antecedent consequence" association rules, which some scholars apply to their text feature extraction (Xu *et al.*, 2013) and further put forth optimization methods. For example, they may use point-wise mutual information (PMI) to expand the product features (Chong *et al.*, 2010), while using term frequency–inverse document frequency (TF-IDF) and variance selection statistical methods (Li *et al.*, 2017) and even a co-occurrence matrix (Sayali, 2015), to pre-select the features. A sequence pattern can describe the semantic and grammatical relationships between words; scholars apply this to text feature extraction (Yu *et al.*, 2017). In recent years, topic models have been widely used in online review feature extraction and classification (Zhang and Liu, 2014), especially those based on LDA (Xu *et al.*, 2015), probability models (Santu *et al.*, 2016) and clustering (Su *et al.*, 2008; Wang *et al.*, 2013).

The method based on dependency first analyzes the dependency of words in sentences and then applies rules and algorithms to extract features from the established dependency (Yamina and Lazhar, 2016). The method's biggest advantage is extracting low-frequency feature words and emotional words, and it can be applied to a large corpus as well. Significant progress has been made in text feature extraction; however, certain problems remain. On the one hand, as the selection of dependency rules significantly affects the results of feature extraction, it is important to find appropriate rules. On the other hand, when evaluating entities, the expression of users is specific. They do not deliberately abide by grammatical rules and language constraints, indicating that the method based on a dependency relationship includes some deviation.

Author	Factors discovered/studied
Liu *et al.* (2019)	Competence, communication, treatment, convenience
Ryskina *et al.* (2020)	Perceived attitudes, communication, clinical expertise
Detz *et al.* (2013)	Personality traits, technical competence, communication, access to physician, office staff/environment, coordination of care
Menon (2017), Li *et al.* (2019a, b)	Reputation, expertise
Asanad *et al.* (2018)	Patient–physician experience, medical and surgical treatment, office staff and analysis of worth
Orhurhu *et al.* (2019)	Knowledgeable, helpful and caring
Li and Hubner (2019)	Technical skills and interpersonal skills
Lagu *et al.* (2019)	Communication and interpersonal skills, technical skills, facility/office experience, staff characteristics, patient care, feedback about survey

Table 1.
Factors discovered in previous related works

To reduce this deviation, a few studies combined this dependency method and the network analysis to find the relationship between candidate feature words and emotion words to construct a network structure with words as nodes and their relations as edges. Then, they calculate a node's importance via the network analysis method, and finally, select features based on their ranking of importance. Lei *et al.* (2010) calculate the importance of candidate feature words by building a bipartite graph between candidate feature words and emotional words and utilizing the hyperlink-induced topic search (HITS) algorithm of webpage ranking. Liu *et al.* (2018) combine PMI and a weighted HITS algorithm to sort candidate feature words on this basis. Meanwhile, Yan *et al.* (2015) build a network structure of "feature words emotional words" based on a dependency syntactic analysis, and then apply the PageRank algorithm for feature extraction. This method of constructing a network with feature and emotion words to analyze node importance provides a reference for this study's feature extraction method.

Each method has its advantages and disadvantages for various corpus characteristics and research purposes. In this study, the processing of physician reviews on OMC platforms involves text feature extraction and sentiment analysis. Hence, the modifiers of each feature word must be extracted to calculate their sentiment value. Therefore, a method based on the dependency relationship is selected. At the same time, by combining the ranking method of frequent words and network analysis to extract features, this method can also rank the importance of features and establish a foundation for sentiment analysis to improve the research's efficiency.

3. Study 1: identifying the influencing factors of doctor consultation volume

In this study, we extracted service features from physician reviews. These features reflect the factors that patients cared about, which would influence their choices when selecting a doctor on an OMC platform. The sentiment values of the obtained service features were then calculated, which represented patients' satisfaction with the corresponding service features.

The working flow of this study is illustrated in Figure 1.

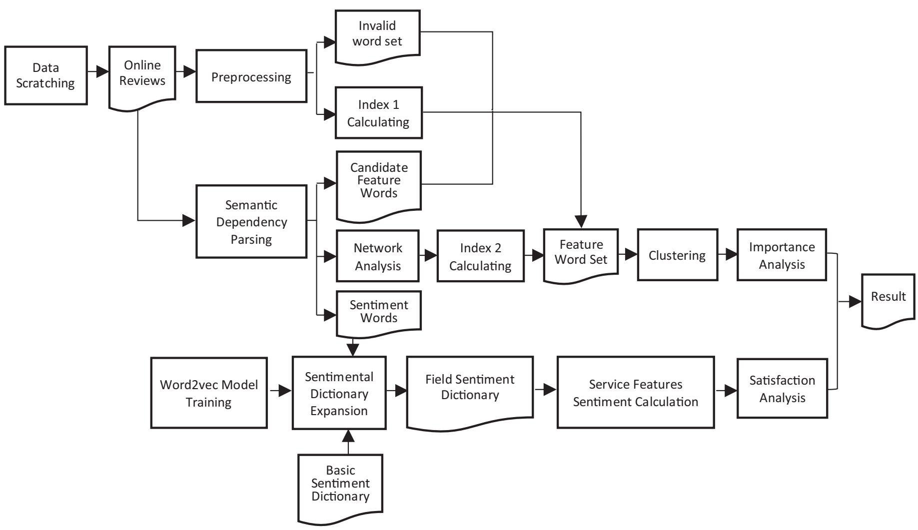

Figure 1.
Data processing flow

3.1 Data scratching

After comparing several OMC platforms, “Dingxiang Doctor” (www.dxy.com) was selected as the data acquisition source for this analysis because it displayed a large number of physician reviews about patients’ online medical consulting and had many medical departments available. This study mainly used the Python crawler technology to capture physician reviews. For the static page, i.e. with the generation of HTML code, the content and display effect of the page are basically determined and will not change. The content of the page is regular, the Requests toolkit can be used to directly obtain all the information of the page in the form of JSON, and then obtain the required information by parsing JSON. For dynamic pages, the content displayed on the page may change with time, environment or database operation results. Intuitively, it is a page that contains a slider and needs to slide down continuously to obtain complete information. The WebDriver toolkit can be used to set up a simulation browser to simulate, operate and control the page through code, and achieve complete page information acquisition.

This section mainly includes the following four steps: (1) Analyze the website structure and webpage characteristics. The structure of the online consultation module of www.dxy.com from outside to inside is the department list page, the doctor list page of each department, doctor’s details page and doctor’s reviews page, which are all dynamic pages. The structure of the doctor’s review page is stable, and its URL can be generated from the URL of the doctor’s details page. (2) From the department list page, obtain the link of each department’s doctor list page, and further obtain the URL of all doctors’ details page and review page. (3) Obtain the basic information of doctors and doctors’ reviews: because the number of doctors dynamically loaded each time on the doctor list page is fixed, the loaded page is regarded as a static page. Therefore, the method of requests for page source code and parsing JSON source code is used to capture the basic information of doctors; the results are written into a CSV file. Then, the WebDriver simulation browser is used to enter the review page from the doctor’s details page, and the sliding of the page to continuously load the reviews is simulated to extract all the reviews of each doctor; the results are written into the text file. (4) Integrate the doctor information and reviews captured in the previous step to make them corresponding and store them in the CSV file to build a complete original dataset of this study.

As of December 2018, we collected more than 200,000 physician reviews from www.dxy.com, corresponding to more than 2,700 doctors, including doctors’ basic information, such as their name, gender, department, hospital, professional title, working years, consultation price, number of reviews, consultation volume and average reply time.

3.2 Service feature extraction

After the online data had been scratched, the corpus was preprocessed using a Python Kit called JIEBA with word segmentation, part-of-speech tagging, word frequency counting and the acquisition of proper nouns and entity words, to obtain an invalid word set and calculate the frequency index 1 (i.e. %count), as shown in equation (1). This represents how frequently these words were mentioned by the patients in their reviews.

Next, dependency parsing via a “Stanford Dependency Parser” was conducted and feature–opinion pairs from a specific dependency relationship were extracted. Three types of dependency relations were selected from the result (“NSUBJ,” “XCOMP” and “AMOD”), which indicates subject-verb, verb-adverb and noun-adjective relations between words in a sentence, respectively. They all describe the relationship between the modification and being modified. The modified words are generally nouns and verbs, and the modifier words are generally adjectives and adverbs. We then separated the modified terms as the candidate feature words and the modifiers as the candidate sentiment words. Finally, 15,447 relations, 3,888 candidate feature words and 1,924 candidate sentiment words were identified.

Then a "feature–modifier" network was built from the dependency relationship. In the network analysis, the PageRank algorithm was applied to the network to calculate Frequency index 2 (i.e. PR), as shown in equation (2). This indicates the importance of the word in the network. We combined Frequency indices 1 and 2 as an index named IP to calculate each word's importance. IP refers to the weighted sum of indexes 1 and 2 with a weight of 0.5, as shown in equation (3).

$$\%\text{count}_i = \text{count}(w_i)\Big/\sum\text{count}(w_n), \quad i = 1, 2, 3, \ldots, n \tag{1}$$

Note(s): W_i: word$_i$; w_n: word$_n$

$$\text{PR} = \alpha * M * \text{PR} + (1 - \alpha)\text{PR} \tag{2}$$

$$\text{IP} = 0.5 * \%\text{count} + 0.5 * \%\text{PR} \tag{3}$$

As a result, we obtained a feature word set with 972 words by filtering the candidate feature words with an invalid word set and IP. Then, the K-means algorithm was applied to the first 100 feature words sorted by index IP. When clustering, parameter K was tested to be 2 to 25. The optimum K was determined by two metrics measuring clustering effects, contour coefficient and covariance between groups, as shown in Figure 2. The optimum K was then set to 14 when the contour coefficient and covariance between groups were all considered to be optimum. The contour coefficient reflects the cohesion and separation degree of the cluster, and its value is between [−1, 1]. When the value is closer to 1, it implies that the distance within clusters is smaller, and the distance between clusters is larger; thus, the clustering effect is superior overall. The covariance between groups reflects the distance between the K clusters; the larger the value, the better the clustering effect.

Table 2 displays the 14 clusters with their ID and feature words. We assigned a name to each cluster based on the meanings of the words in each cluster. They were professional title, professional knowledge, diagnosis, sickness explanation, treatment plan, treatment effect, personality traits, patient care, trust, response, phraseology, word of mouth, platform and overall service experience. Professional knowledge included such keywords as "experience," "knowledge" and "professional knowledge," and described the objective professional knowledge that doctors mastered. Diagnosis included keywords such as "diagnosis," "symptoms," "problems" and "reasons," describing a doctor's accurate diagnosis of a patients' condition. Sickness explanation included keywords, "interpretation," "explanation," "description" and "understanding," which described the process that a doctor explained the

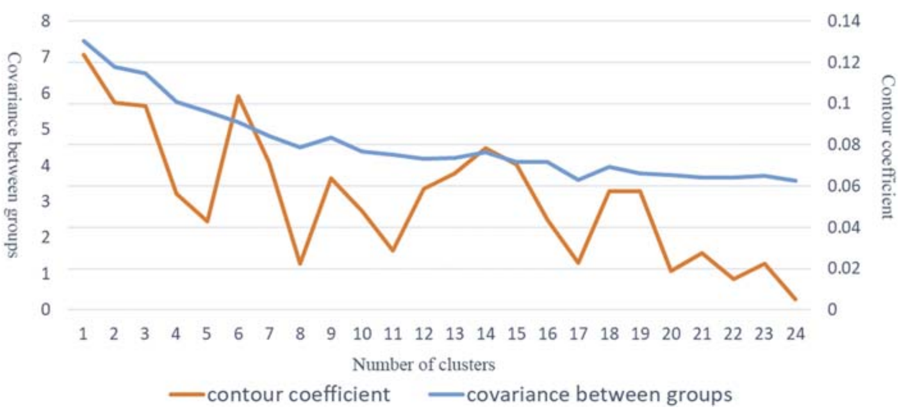

Figure 2. Polyline diagram of clustering effect and parameter K

Table 2.
Cluster and the examples of included feature words

ID	Name	Feature words (for example)
0	Professional title	教授 (professor), 主任 (director), 专家 (expert)
1	Professional knowledge	经验 (experience), 知识 (knowledge), 能力 (ability), 专业性 (professionalism), 专业知识 (professional knowledge)
2	Diagnosis	病情 (disease), 诊断 (diagnosis), 症状 (symptoms), 检查 (examination), 问题 (problems), 原因 (reasons)
3	Sickness explanation	解读 (interpretation), 解释 (explanation), 逻辑 (logic), 描述 (description), 理解 (understanding)
4	Treatment plan	解决方案 (solutions), 处方 (prescription), 手术 (operation), 药物 (medicine)
5	Treatment effect	好转 (improvement), 缓解 (alleviation), 恢复 (recovery), 效果 (effect)
6	Personality traits	医术 (medical techniques), 好人 (good person), 责任心 (responsibility)
7	Patient care	安慰 (comforting), 鼓励 (encouraging), 态度 (attitude), 沟通 (communication)
8	Trust	信任 (trust), 信任感 (trustworthiness), 信心 (confidence)
9	Response	回答 (answering), 回复 (reply), 询问 (enquiry), 追问 (questioning), 回应 (response)
10	Phraseology	语言 (language), 表述 (expression), 语气 (tone), 话 (words)
11	Word of mouth	好评 (comment), 评价 (evaluation), 值得 (worth), 力荐 (recommendation)
12	Platform	平台 (platform), 信息 (information)
13	Overall service experience	体验 (experience), 服务 (service), 咨询 (consultation)

disease to a patient. Diagnosis, treatment plan and treatment effects described doctors' abilities and therapeutic effects in the consultation process according to patients' disease information. The results illustrated that patients paid more attention to a doctor's practical problem-solving ability and service in an OMC environment. The features of personality traits, patient care, response, phraseology, experience and word of mouth describe patients' perceptions of doctors' attitudes and services.

For the remaining feature words, we calculated the similarities between them and the words contained in each cluster based on the word2vec model. They were then assigned to the clusters (shown in Table 2) that were most similar to them. As a result, we obtained service features of online medical consulting services and the feature words included in each service feature. These service features indicate the aspects that patients care about in OMCs.

We conducted a significance analysis of each service feature according to the number of words in each service feature and the importance index of each feature word. This also indicated the patients' attention to this feature. The number of feature words contained in each service feature, and its importance index is shown in descending order in Table 3. The top five service features are trust, phraseology, overall service experience, word of mouth and personality traits. It is interesting to note that these features describe a doctor's soft skills and services, indicating that patients pay more attention to doctors' soft skills and overall service experience. Trust, the first important service feature, is not only an important guarantee mechanism for the online environment (Bauman and Bachmann, 2017), but is also an important factor in promoting doctor–patient relationships and achieving good medical outcomes (Corritore *et al.*, 2012). Therefore, trust has become the most important feature of OMC (which combines the dual characteristics of the online environment and medical services). Given the important role of trust in OMC, and generally in research models that consider specific antecedent and consequence variables, online trust is usually considered a mediator (Kim and Peterson, 2017). Many studies have explored the antecedents and consequences of online trust (Beldad *et al.*, 2010). The features of products or services on online platforms are antecedents that affect patients' online trust and, thus, their transaction intentions (consequences). Therefore, in the following study on the influence model of doctor's consultation volume, we also consider trust as a mediating variable.

	Service feature	Feature words volume	Average_% Count	Average_% PR	Average_IP
1	Professional title	24	0.000158	0.000201	0.000179
2	Professional knowledge	87	0.000061	0.000158	0.000109
3	Diagnosis	110	0.000022	0.000094	0.000058
4	Sickness explanation	60	0.000171	0.000087	0.000129
5	Treatment plan	96	0.000031	0.000055	0.000043
6	Treatment effect	59	0.000202	0.000261	0.000231
7	Personality traits	103	0.000357	0.000313	0.000335
8	Patient care	99	0.000107	0.000110	0.000109
9	Trust	19	0.001255	0.001531	0.001393
10	Response	97	0.000101	0.000106	0.000104
11	Phraseology	81	0.002155	0.000372	0.001264
12	Word of mouth	29	0.000758	0.000627	0.000692
13	Platform	27	0.000102	0.000094	0.000098
14	Overall service experience	81	0.001649	0.000432	0.001041

Note(s): importance index means the index which reflect the importance of each service feature; Average_% Count is one of the importance indexes and is calculated by word frequency; Average_%PR is another importance index, which is calculated by node importance; Average_IP is the weighted average of Average_% Count and Average_%PR

Table 3. Average importance index of service features

3.3 Sentiment analysis of service features

According to the results above, 1,924 candidate sentiment words were identified. First, we obtained the sentiment word set by filtering candidate sentiment words with an invalid word set and removing the nouns. Second, we expanded the basic sentiment dictionary to obtain a field sentiment dictionary. To expand the dictionary, we chose the Dalian technology sentiment vocabulary ontology, which contains rich sentiment words and ontology as the basic sentiment dictionary. For the sentiment word that did not exist in the basic dictionary, we found the basic sentiment word in the dictionary that had the smallest distance with the sentiment word according to the trained word2vec model and semantic similarity. The sentiment value of the word in the dictionary was directly utilized for the word that did not exist in the dictionary. Therefore, we obtained the sentiment value of all sentiment words. The values of words with negative emotions were −1, −3, −5, −7 and −9, while positive emotions were listed as 1, 3, 5, 7 and 9. Third, we calculated the sentiment value for each feature word according to the "feature-modifier" network. This is the sum of the sentiment values for all modifiers that were connected to the feature word. Finally, we calculated the sentiment value of each service feature, i.e. the sum of the sentiment values of the feature words contained in the service feature was divided by the number of feature words therein.

As Table 4 shows, the average sentiment values of each feature are positive, indicating that patients are generally satisfied with the OMC service provided on dxy.com. The average sentiment value of all the feature words is 24.06, and out of the 14 features, only the average value of the following five features is higher than the average of 24.06: response, treatment plan, personality traits, diagnosis and title. Most of these five features describe doctors' professional capabilities. This shows that the professional capability of doctors on the OMC platform can sufficiently meet the needs of patients, whereas other aspects of doctors' performance (mostly services) are not as good as their professional capabilities.

Table 4. Average sentiment value of each cluster

Cluster	No. of feature words	Sentiment value	Average sentiment value
Professional title	20	482	24.10
Professional knowledge	84	1,484	17.67
Diagnosis	106	2,666	25.15
Sickness explanation	58	1,219	21.02
Treatment plan	91	3,106	34.13
Treatment effect	56	949	16.95
Personality traits	96	2,939	30.61
Patient care	95	1,915	20.16
Trust	18	294	16.33
Response	93	3,585	38.55
Phraseology	77	999	12.97
Word of mouth	28	555	19.82
Platform	27	475	17.59
Overall service experience	74	1,539	20.80
Total	923	22,207	24.06

Note(s): Average sentiment value is calculated by dividing the number of feature words by sentiment value

4. Study 2: influencing mechanism of doctor consultation volume

Based on the above results, this study builds the influence model of doctors' consultation volume. We first discuss the influence of various service features on trust and then explore the influence of trust as well as other control variables on doctors' consultation volumes.

4.1 Descriptive statistical analysis of doctor information

From the website, we can obtain not only physician reviews, but also the personal information of doctors, such as their scores, working years, average reply time, consultation price, number of reviews and consultation volumes. Through the descriptive statistical analysis of doctors' information, we developed a certain understanding of the basic information of doctors on the OMC platform (Table 5). First, the average score of doctors was 4.79 out of 5.0, and the standard deviation was small, indicating that patients generally rated doctors highly and experienced a high degree of satisfaction with the overall service provided by them. Second, the average number of working years was 12.5, indicating that doctors on this OMC platform generally had satisfactory professional experience. In terms of the average reply time, the mean value was 1.37 h, indicating that, on average, patients had to wait for more than 1.5 h for a reply after submitting a consultation request. Third, the average consultation price was RMB39, and the standard deviation was 37.49. The large standard deviation indicates that there is a significant difference in consultation prices. Fourth, the average number of reviews of each doctor was 87.49, indicating that patients on the platform were active and generally willing to comment on their doctor's services after their

Table 5. Descriptive statistical results of physician information

Doctors' information	Maximum	Minimum	Mean	STD
Score	5.0	0.0	4.79	0.69
Working years	43	2	12.46	6.77
Average reply time	18.45	0.02	1.37	1.67
Consultation price	600	10	39.01	37.49
Number of reviews	3,908	0	87.49	228.93
Consultation volume	20,830	0	694.31	1344.42

consultation. Finally, doctors' average consultation volume was 694, indicating that doctors generally had a high consultation volume and were active on this platform. The standard deviation of consultation volume was large (1344.42), indicating that the consultation volume between doctors remains uneven; this implies that there is room for improvement for some doctors.

We also analyzed the distribution of doctors' professional titles and consultation volumes, as shown in Figure 3. Residents and attending doctors accounted for 71% of the total number of doctors and 76% of the total consultation tasks. This indicates that doctors with low professional titles should not be underestimated in terms of both the number and their responses to patients' consultations.

4.2 Descriptive statistical analysis of the service features

By carrying out descriptive statistics on the sentiment value for each service feature, we can establish a certain understanding of patient satisfaction with the service features (Table 6). The average value for each service feature's sentiment value is greater than zero, indicating that overall, patients were satisfied with each service feature. The minimum values were all less than zero, indicating that in each service feature, there were some doctors whose patients were dissatisfied with their services. Some service features had a high sentiment maximum value, such as phraseology (2,782) and platform (3,413), indicating that some doctors have many positive reviews on these features. In general, each service feature's standard deviation was large, such as word of mouth (mean 8.15, STD 23.73) and personality traits (mean 7.50, STD 21.56), indicating that there are significant differences in patients' satisfaction with each doctor in each service feature.

4.3 The effect of service features on trust

Numerous studies have explored the antecedents and consequences of online trust (Beldad *et al.*, 2010). The features of products or services on online platforms are antecedents that affect users' online trust and consequently, their transaction intentions (consequences). Du *et al.* (2020) found that doctor–patient communication, service quality and patient service satisfaction have a positive impact on doctor–patient trust. Gu *et al.* (2019) found that in

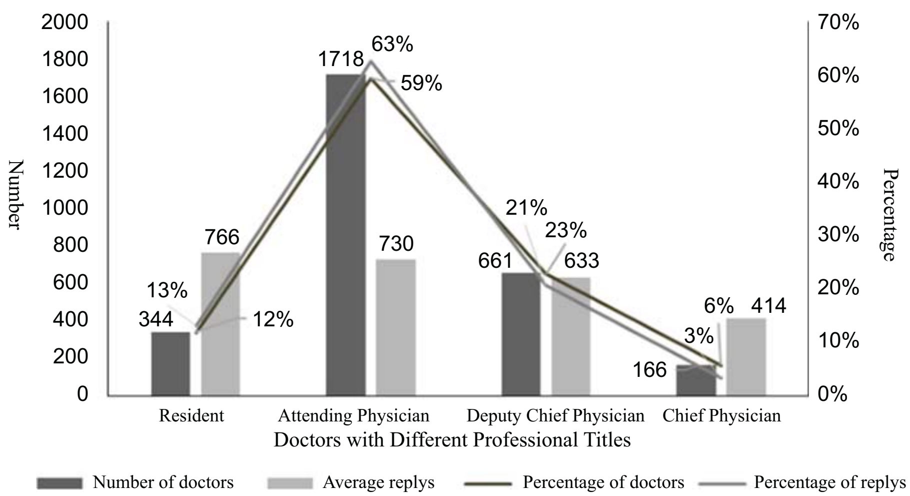

Figure 3.
The distribution of number and reply times of doctors with different professional titles on "Dingxiang doctor" platform

Table 6.
Descriptive statistical analysis results of service features

Service features	Numbers	Minimum	Maximum	Mean	STD
Professional title	233	−37	112	0.77	4.60
Professional knowledge	718	−7	262	4.16	12.53
Diagnosis	368	−5	78	1.16	4.52
Sickness explanation	222	−8	41	0.53	2.62
Treatment plan	252	−5	32	0.54	2.13
Treatment effect	732	−10	225	3.34	11.05
Personality traits	1,062	−7	343	7.50	21.56
Patient care	847	−7	257	5.62	16.72
Trust	1,158	−5	395	8.07	22.11
Response	407	−7	130	1.17	5.06
Phraseology	1,938	−14	2,782	54.26	158.58
Word of mouth	1,174	−9	512	8.15	23.73
Overall service experience	274	−3	43	0.33	1.88
Platform	120	−5	3,413	6.87	205.39

village clinics, doctors' communication skills affect patients' trust in doctors. Suki (2011) found that patients' satisfaction and doctors' reputations positively affected patients' trust in doctors in offline medical services. Isangula *et al.* (2020) through qualitative investigation found that doctors' interpersonal behavior and professional ability were the two main factors affecting patients' trust. Therefore, we believe that patient satisfaction with the service features of doctors will affect patients' trust in doctors.

We consider that the sentiment value of trust is a dependent variable, while the sentiment values of other service features are independent variables. According to the research of Little and Rubin (2002) and Benson *et al.* (2021), the missing value was filled with the average sentiment value of other doctors in this service feature. According to this part's research purpose, the independent variable was adjusted based on the following points: (1) When we first regress all the service features and trust, we find that the collinear coefficient variance inflation factor (VIF) of "phraseology" and "overall service experience" are both greater than 10 (Appendix 1). Therefore, we combined these two factors into one variable, named "phraseology and experience," to avoid multiple collinearity problems. (2) Feature "platform" was not considered in the equation because it mainly described characteristics of the platform, such as its usability and availability of information, whereas Study 2 primarily explores the influence of doctors' service features on patients' trust. (3) "Professional title" was not considered as an independent variable, because the doctors' information obtained from the website includes their titles, and it had the same meaning as the "professional title" in the extracted service features. Thus, the measurement model between the service features and trust is shown in equation (4):

$$\begin{aligned} \text{trust} = \beta_0 &+ \beta_1 \text{professional knowledge} + \beta_2 \text{diagnosis} \\ &+ \beta_3 \text{sickness explanation} + \beta_4 \text{treatment plan} \\ &+ \beta_5 \text{treatment effect} + \beta_6 \text{personality traits} \\ &+ \beta_7 \text{patient care} + \beta_8 \text{response} + \beta_9 \text{word of mouth} \\ &+ \beta_{10} \text{phraseology and experience} \end{aligned} \quad (4)$$

The results of this model are presented in Table 7. From Table 7, we can see that, except for professional knowledge, diagnosis and sickness explanation, the other seven service features had significant positive influences on trust. This shows that patient satisfaction with the service features of doctors affects patients' trust in doctors. Doctors can improve these service features to improve patient trust. Professional knowledge had no significant effect on trust.

	Unstandardized coefficient		Standardized coefficient			Collinearity diagnosis	
	B	Std. error	Beta	t	Sig	Tol	VIF
Constant (C)	−0.028	0.005		−5.993	0.000		
Professional knowledge	0.006	0.017	0.005	0.375	0.707	0.388	2.577
Diagnosis	−0.020	0.015	−0.017	−1.346	0.178	0.419	2.387
Sickness explanation	0.014	0.013	0.011	1.071	0.284	0.649	1.541
Treatment plan	0.081	0.012	0.061	6.668	0.000	0.813	1.230
Treatment effect	0.053	0.019	0.043	2.741	0.006	0.279	3.588
Personality traits	0.263	0.019	0.291	13.914	0.000	0.156	6.393
Patient care	0.096	0.017	0.107	5.799	0.000	0.203	4.922
Response	0.157	0.020	0.098	7.988	0.000	0.460	2.174
Word of mouth	0.102	0.025	0.085	4.121	0.000	0.161	6.210
Phraseology and experience	0.306	0.022	0.346	13.657	0.000	0.107	9.369

Table 7. Results of the model between service features and trust

This indicates that in the OMC environment, patients pay more attention to a doctor's actual performance in the consultation process and place more emphasis on whether they can provide appropriate feedback, based on the graphic information provided online by patients.

4.4 The effect of trust on consultation volume

In this model, trust is considered an independent variable. The doctor's consultation volume is considered as a dependent variable. Correlation analysis of doctors' number of reviews and consultation volume shows that these two have a strong positive correlation (0.860, see Appendix 2) and are not direct causality, but mutual causality. Therefore, we conducted a regression analysis using the backward method with all the ordered and numerical variables in the doctor information as control variables, except for the number of reviews (Table 8). It was found that only consultation price and trust had significant effects on the doctor's consultation volume, so Model 6 was considered as the final model, as shown in equation (5):

$$\text{consultation volume} = \beta_0 + \beta_1 \text{trust} + \beta_2 \text{consultation price} \tag{5}$$

The results of this model are presented in Table 8. From Table 8, we can see that trust has a significant positive influence on consultation volume. This implies that trust plays a mediating role between service features and a doctor's consultation volume. Service features first affect patients' perceived trust in a doctor, and subsequently, the doctor's consultation volumes. Among the control variables, consultation price had a significant negative influence on a doctor's consultation volume.

5. Conclusion

The availability and accessibility of medical resources has always been a challenge worldwide. OMC platforms are a solution to these problems. This study proposes an automated text mining framework for extracting the features that patients pay attention to from physician reviews, to improve the popularity of doctors on OMC platforms and promote the development of these platforms. Furthermore, the influencing mechanisms of these factors on a doctor's consultation volume are analyzed.

This study found 14 service features from physician reviews: professional title, professional knowledge, diagnosis, sickness explanation, treatment plan, treatment effect, personality traits, patient care, trust, response, phraseology, word of mouth, platform and

Table 8.
Results of the model between trust and consultation volume

Model		Unstandardized coefficients B	Std. error	Standardized coefficients Beta	t	Sig
1	(Constant)	9127.664	14081.202		0.648	0.517
	Department	−1.059	4.319	−0.005	−0.245	0.806
	Sex	20.883	58.794	0.007	0.355	0.723
	Title	−111.565	64.775	−0.045	−1.722	0.085
	Working years	−4.032	6.947	−0.015	−0.580	0.562
	Average reply time	−0.171	0.357	−0.009	−0.478	0.633
	Trust	47.426	1.100	0.807	43.109	0.000
	Consultation price	−5.528	1.032	−0.105	−5.357	0.000
2	(Constant)	9217.663	14069.966		0.655	0.513
	Sex	20.892	58.767	0.007	0.356	0.722
	Title	−111.228	64.731	−0.045	−1.718	0.086
	Working years	−4.083	6.940	−0.015	−0.588	0.556
	Average reply time	−0.170	0.357	−0.009	−0.477	0.633
	Trust	47.456	1.093	0.807	43.427	0.000
	Consultation price	−5.533	1.031	−0.105	−5.365	0.000
3	(Constant)	9278.124	14062.947		0.660	0.510
	Title	−111.977	64.669	−0.045	−1.732	0.084
	Working years	−4.106	6.937	−0.015	−0.592	0.554
	Average reply time	−0.182	0.355	−0.009	−0.512	0.609
	Trust	47.460	1.092	0.807	43.453	0.000
	Consultation price	−5.529	1.031	−0.105	−5.364	0.000
4	(Constant)	9305.879	14057.788		0.662	0.508
	Title	−112.401	64.641	−0.045	−1.739	0.082
	Working years	−4.126	6.934	−0.015	−0.595	0.552
	Trust	47.500	1.089	0.808	43.614	0.000
	Consultation price	−5.582	1.025	−0.106	−5.444	0.000
5	(Constant)	942.605	153.126		6.156	0.000
	Title	−86.735	48.125	−0.035	−1.802	0.072
	Trust	47.502	1.089	0.808	43.629	0.000
	Consultation price	−5.516	1.019	−0.105	−5.413	0.000
6	(Constant)	683.233	52.373		13.046	0.000
	Trust	47.607	1.088	0.810	43.741	0.000
	Consultation price	−6.077	0.971	−0.116	−6.255	0.000

Note(s): Dependent variable: consultation volume

experience. Further exploring patients' attention to these service features, we found that patients pay more attention to doctors' soft skills in the OMC process, such as trust, phraseology, patient care, word of mouth and personality traits, which is unique to OMC platforms. Through sentiment analysis of these service features, we obtained patients' degree of satisfaction with each service feature. The results show that patients are more satisfied with doctors' service features, such as response, treatment plan, personality traits and diagnosis. Except for personality traits, we find that the features that patients are more satisfied with are not those that patients often discuss, which indicates that patients may be more willing to post reviews related to negative experience than positive experience.

Trust is not only an important guarantee mechanism in the online environment but also the cornerstone of the doctor–patient relationship. Therefore, it is particularly important to establish a trusting relationship between doctors and patients in OMCs. According to the theoretical basis of online trust, this study considers trust as the mediating variable, reorganizes the remaining 13 features and obtains ten antecedents (professional knowledge, diagnosis, sickness explanation, treatment plan, treatment effect, personality traits, patient care, response, word of mouth, as well as phraseology and experience) that affect patients trust in doctors so as to build the influence mechanism model of patients' choice of doctors in OMC. It also explores the doctors' service features that can affect patients' trust. The results show that treatment plan, treatment effect, personality traits, patient care, response, word of mouth, as well as phraseology and experience affect doctor consultation volumes by influencing patient trust in doctors.

6. Discussion and future research

We believe that this research is an important step that can help doctors understand which features they should improve to increase their consultation volumes on OMC platforms. This study complements existing trust research in the field of OMC by showing how individual physician service features affect patients' trust in physicians and how this, in turn, affects a physician's consultation volumes. These results not only provide suggestions for doctors but also contribute to the development of OMC platforms that play an important role in solving the problem of shortage and the unbalanced distribution of medical resources.

6.1 Theoretical contributions

Although there have been some OMC studies, we have provided novel information and relevant implications through this research. First, because physician reviews are generated by patients, they not only truly reflect the needs and desires of patients, but also provide comprehensive information. Therefore, we extract the service features that patients focus on from physician reviews so that the information provided by our results can be considered authentic, accurate, comprehensive and detailed. We discovered four new service features: sickness explanation, diagnosis, platform and overall service experience. This study also calculated patients' attention and satisfaction with each feature, which pointed out how doctors could attract patients and improve patient satisfaction.

Second, the service feature extraction method proposed in this study provides a solution for text analysis problems that require both the extraction of features and aspect-level sentiment analysis. It combines the PageRank algorithm with frequent word extraction, considering both word frequency and node importance in feature word identification. This ensures that words with less frequency and greater importance will not be missed in feature extraction. Moreover, this study improves the accuracy of sentiment analysis of service features by forming a more comprehensive and applicable emotion dictionary in this field. The emotion dictionary was built by expanding the basic emotion dictionary based on the word2vec model and semantic similarity. The method proposed in this study can also be applied to other online review analyses.

Finally, this study used two regression models to prove the mediating role of trust between other service features and a doctor's consultation volumes. This result not only enriches current trust-related research in the field of OMC, which has a certain reference significance for subsequent research on the establishment of trust in online doctor–patient relationships but also provides a reference for research concerning the antecedents of trust in general.

6.2 Practical implications

Based on the above analysis and conclusion, we recommend some suggestions for doctors to improve their service attractiveness, thereby increasing their consultation volumes. These suggestions will not only improve the ability of doctors to meet patients' needs on an OMC platform, thereby improving patients' consulting experience, but also promote the development of OMC platforms and alleviate the imbalance in medical resource allocation.

Specifically, the following suggestions are proposed:

First, patients pay more attention to the features describing doctors' soft skills and are not generally satisfied with them. Therefore, doctors should focus on improving their soft skills and characteristics. For example, patients care about features such as patient care and response. Thus, when doctors conduct consultation services for patients, they should pay attention to the details to reflect a positive attitude toward patients and adhere to medical ethics while providing appropriate emotional care and comfort. Furthermore, patients care about phraseology, so it is necessary to pay attention to the language used in communication with patients and avoid the repetition of nonsense, incorrect words, or words that sound too verbose or brief. Moreover, patients care about word of mouth, so doctors should encourage patients to comment and record their feelings in their reviews.

Second, patients care about overall service experience, so doctors should improve their understanding of OMC characteristics and strengthen their ability to provide good overall service for patients on OMC platforms. Compared to traditional offline medical consultations, OMCs do not have the conditions that allow for face-to-face communication and checking of test results. Thus, this process is more about diagnosing patients' symptoms through text, voice, pictures, videos and other media, and then communicating to patients through these media. Therefore, while strengthening their professional abilities, doctors also need to combine OMCs' characteristics with regard to exercising their abilities, from mastering their understanding of symptoms to diagnosing diseases and formulating both diagnosis and treatment plans during the OMC process. In addition, to better adapt to the online environment, doctors should strengthen their utilization of multimedia channels when explaining diseases, diagnoses and treatment plans to patients. In doing so, they must reasonably show patients their professional qualities through OMC service processes and build patient trust. Thus, patients can be encouraged to post positive comments, which form a virtuous circle that improves doctors' consultation volume.

Third, doctors should build patients' trust through the information displayed on OMC platforms. Trust is a service feature that ranks first in terms of attention but last in satisfaction. This indicates that trust based on online information has an important impact on patients' decisions when choosing a doctor. However, currently, patients' trust is generally low. Therefore, doctors should pay attention to the various types of information displayed on OMC platforms. Not only should they adjust how information is displayed and expressed to highlight their advantages, but they also need to build trust with patients in the consultation service process to promote patients' posts of positive comments, to build a good reputation and increase consultation volume.

Fourth, in addition to the features of doctors, patients also care about the platforms. Therefore, it is important to optimize OMC platforms, as their overall service capability is the basis for creating a satisfactory patient experience and improving doctors' consultation volumes. This could also help attract more patients to engage with the OMC platforms and more doctors to enter this service (thereby promoting the development of OMC), thereby alleviating the pressure of diagnosis and treatment in traditional offline medical institutions, and the unreasonable allocation of medical and health resources and meeting the growing demand for medical consultation.

6.3 Limitations and future research

In future studies, more detailed analyses could be carried out to refine some results of this study. First, in the sentiment analysis of service features, the polarity and intensity values of emotional words were considered, but the influence of degree adverbs on emotional intensity values was not considered. Therefore, the aspect of emotional calculation should be refined in future studies. Second, cultural uniqueness may have a potential influence on the result. Wang *et al.* (2019) found that consumers with different cultures concentrate on different product features. There may be differences in doctor reviews in different countries and cultures. The methods introduced in this study can be used to explore whether there are differences in the results in different cultures. Due to cultural uniqueness, in the context of this study, much of the patients' comments were positive. Many studies have found that negative user comments have a greater impact on consumers than positive comments (Luo *et al.*, 2018; Weisstein *et al.*, 2017). Future research can focus on negative comments on OMC platforms. Third, this study did not distinguish between the effects of chronic and acute diseases. In these two situations, patients may have different concerns. A later study in our lab will divide the disease and patient types (intellectual or emotional) to observe whether they make any difference to the results. Fourth, in addition to the service feature of a doctor, other factors on the OMC platform may affect doctors' consultation volume, such as the additional function of the platform – online and offline service integration (Huang *et al.*, 2021). Therefore, future research can explore other factors that affect doctor trust and consultation volume on OMC platforms.

Note

1. https://m.yicai.com/news/5055809.html

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Appendix 1

Table A1. Results of the model between service features and trust

	Unstandardized coefficient		Standardized coefficient			Collinearity diagnosis	
	B	Std. error	Beta	*t*	Sig	Tol	VIF
Constant (*C*)	−0.027	0.005		−5.718	0.000		
Professional knowledge	0.007	0.017	0.006	0.438	0.661	0.401	2.495
Diagnosis	−0.023	0.015	−0.020	−1.541	0.124	0.416	2.403
Sickness explanation	0.013	0.013	0.011	1.043	0.297	0.646	1.547
Treatment plan	0.079	0.012	0.060	6.486	0.000	0.799	1.251
Treatment effect	0.047	0.019	0.038	2.456	0.014	0.277	3.607
Personality traits	0.251	0.019	0.278	13.158	0.000	0.152	6.560
Patient care	0.091	0.017	0.100	5.361	0.000	0.196	5.106
Response	0.156	0.020	0.097	7.923	0.000	0.455	2.197
Word of mouth	0.079	0.025	0.066	3.119	0.002	0.152	6.571
Phraseology	0.181	0.029	0.198	6.206	0.000	0.067	*14.910*
Overall service experience	0.169	0.027	0.195	6.328	0.000	0.071	*14.008*

Note(s): Italics value means that the VIF of Phraseology and Overall service experience are greater than 10, which indicate that they have multicollinearity

Appendix 2

		Consultation volume	Number of reviews
Consultation volume	Pearson correlation	1	0.860**
	Sig. (2-tailed)		0.000
	N	2,887	2,887
Number of reviews	Pearson correlation	0.860**	1
	Sig. (2-tailed)	0.000	
	N	2,887	2,887

Note(s): **Correlation is significant at the 0.01 level (two-tailed)

Table A2. Correlation analysis results of number of reviews and consultation volume

Corresponding author
Ziqing Peng can be contacted at: pzq@bupt.edu.cn