Understanding Patients' WOM of IT-Enabled Healthcare Service: A Case Study of Online Health Consultation

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Abstract

In healthcare context, the service delivery and information management are facilitated via varieties of IT-Enabled collaborative platforms. The effect of IT-Enabled collaboration health service has been extensively explored in recent decades. However, few studies have investigated the IT-Enabled health service from the perspective of patients or health consumers. Our research fills this research gap through a case study of an online health consultation website. The review systems on the website enable patients to write their word of mouth about services and physicians, thus providing us with a material to understand the interests, motivations and expectations of patients. In this work, we utilize four text-analysis techniques: term frequency analysis, sentiment analysis, feature words clustering and topic modelling to mining information from the textual WOM of patients. The results of our research have both theoretical and practical implications for optimizing the IT-Enabled health service, maintaining a harmonious physician-patients' relationship and increasing patients' satisfaction.

1. Introduction

Heath issue is usually challenging and costly. The government, caregivers and patients are actively exploring methods to control the cost of health care through the evolution of medical technology, the innovation of care delivery channel, the collaboration of healthcare resources and the application of patients management systems[24]. Understandably, patients traditionally turn to physicians, family members or friends for medical or emotional support to deal with their health issues [20]. However, due to the insufficient healthcare resources in developing countries, there are amounts of rural patients have no effective access to healthcare service [12]. In recent decades, the development of information technology brings opportunities to facilitate the healthcare delivery in developing areas. In particular, a fast growing number of telemedicine programs have been established around the world [25]. The concept of telemedicine emerged approximately four decades ago, basically devoted to promote the collaboration among health professionals and technologists via telecommunications and bio-medicine technology to support remote patients care or health service collaboration [24]. Currently, as the advance of a variety of Internet and communication technologies (ICT), the flexibility and accessibility of online resources attract more and more patients to turn to the Internet to seek information, healthcare service and social support [32] as they played an energetic role in the process of making decisions about their health care and treatment. For example, the search engine has been commonly used to search for information support about health concerns [40]. Similarly, the social network and online communities attract more and more patients to communicate about their health issues [42]. Specifically, the widespread adoption of online health communities (OHCs) make a great difference in the transformation of the experiences of healthcare such as peer-to-peer support , chronic disease management and information collaboration among patients, caregivers, health professionals, and policy makers [21]. In the early stage of OHC, its participants are usually health consumers. Through engaging in health issue related discussion online, they gain external information support and emotional support from similar patients [44]. Now, the participation of health professionals extend the schema of online health communities by means of providing online health consultation, clarifications, explanations, as well as possible reference, resources, and opinions about medical issues, remedies, and therapies for patients and other health consumers [18]. As a consequence, websites or forums providing 'e-Health services' emerge one after another. In China, there are some famous online health websites, for example, the Haodf.com (http://www.haodf.com/)

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and the Guahao.com (http://www.guahao.com/). Those websites utilize interactive communication and information technology to bridge the gap between healthcare consumers and caregivers. Through enhancing the physician-patient relationship and providing access to valued resources that can be shared among members, they advocate the information and service collaboration among health professionals, researchers, patients, and their family members, with the goal of tackling health issues [2]. To date, there have been a large number of studies and systematic literature reviews on IT-Enabled collaboration in healthcare context, ranging from the design of health information systems [6] to the implementation of HIT [36]. Despite previous research, very few studies investigate the users' WOM of the IT-Enabled collaborative health service delivery. As is a consensus that understanding users' needs is fundamental for the design of information systems, designing effective online health platforms using ICT also requires in-depth understanding of users' health service needs. Based on such principle, we propose our main research question:

RQ: What is the user's WOM of the IT-Enabled healthcare service?

To address these issues, we take a famous online health consultation website as a sample to study users' online WOM about IT-Enabled healthcare service. Understandably, users' WOM expressed in natural language are a comparatively rich reflection of their positive attitude and real demand. Through using text analysis method, this study intends to analyze characteristics of user-generated posted reviews after counseling a health professional. Our research contributes to both the research and practice of IT-Enabled collaborative healthcare service, through extending the application of text analysis method in understanding patients' attitude. The case study reveals patients' interest, demand and motivations when using IT-Enabled health service, thus providing practical implications for care providers, policy makers and website designers.

This paper is structured as follows. First, IT-Enabled collaboration in healthcare, online WOM and text analysis method are reviewed. Second, the research context including dataset and method is presented. Result from the case study are presented and explained, followed by the conclusion and discussion describing users' WOM on IT-Enabled healthcare service. Finally, the managerial implications and limitations of the research and suggestions for future research are given.

2. Literature Review

2.1. IT-Enabled collaboration in healthcare and online health consultation

With the growth of information technology, the IT-Enabled collaboration emerged a few decades ago, and has been commonly applied in many field, such as education, work-flow, industry and logistics [1]. Previous study has confirmed the effectiveness of IT-Enabled collaborative method. To balance the unmet healthcare demand and the shortage of healthcare providers and medical resources, government agencies and foundations have increased financial and human resources investment to collaborative projects for health research and education[21], such as telemedicine and Electronic Health Record(EHR). These practices not only facilitate the medical resource allocation and collaboration between developing areas and developed areas, but also allow remote patients to access medical support such as pre-diagnosis and treatment, through the Internet, via computers or wireless devices. In recent years, advances in information and communication technologies (ICT) have raised health consumers' expectations for health. There is an obvious tendency that more and more patients participate in health information seeking, self-management and health decision making. Accordingly, the concepts of Health 2.0 and Medicine 2.0 have been introduced [43]. In this context, ICT offers a promising means to establish unparalleled and direct collaborative interaction between healthcare professionals and patients. As a typical application of IT-Enabled collaboration in healthcare, the online health consultation service provides alternatives to face-to-face consultations in virtue of social media, telephone and live interactive video. Through online health consultation, doctors could not only get money reward but also obtain the social reward, for example, get higher reputation and, improve patient flow [45]. For patients, online health consultation serves as an alternative source of medical support to cope with their illness. This interactive service allows patients to ask questions related to their disease and receive customized therapy based on personal health conditions and disease severity [29]. Although these services are increasing in number, they need to be evaluated for their potential to provide convenient and efficient care for specialty services.

2.2. Online Word-of-Mouth

People often publish their WOM to express their comments on a service or a product. While traditional WOM usually consists of spoken words and exchanged with familiars in a face-to-face situation, online WOM involves personal experiences and opinions transmitted through the written word [41]. The online WOM are popular among electronic commerce website, allowing users' write down their reviews or judge a product based on previous reviews [27].

There have been many researches investigating the effect and of users' WOM. For example, in marketplace, lots of researchers have found that online WOM significantly impacts consumers' consumption behaviors [37], product sales performance [10] and reputation [7]. In service industry, users WOM or reviews also play an important role to influence experiencers decision making such as service evaluation, channel selection [28]. In the IT-Enabled healthcare platforms, WOM are also necessary to help users share their service experience, rank physicians service quality and express satisfaction. Previous studies have devoted much attention to the numeric ratings of physicians have received broad attention from both the media and other physicians [31]. Specifically, researchers have explored the technical ratings and functional ratings of WOM on patients' choice [30]. Compared to numeric ratings, the textual comments could be a more vivid reflection of users' real mind, thus would be an important resource to understand users. However, currently there is a lack of investigation on textual WOM in the context of IT-Enabled healthcare.

2.3. Text analysis method in healthcare context

Text mining techniques have been developed to extract and quantify the textual information and useful knowledge from textual corpus [26]. As it is known, there are some classical text analysis method, which is effective, accurate and generalized in dealing with textual content. For example, the topic modelling and sentiment analysis. are commonly used to mining users opinion and calculate users' emotion valence [34], respectively. Compared to the human-annotated method, these automatic text mining methods are much more efficient and low-cost. Hence, more recently, text mining techniques have been adopted by medical fields, such as extracting terms from clinical text [17], analyzing medical research publications to match domain ontology [9] and investigating the effect of sentiment features in locating the online mentions of adverse drug reactions [23]. Specifically, through studying users' online posts (i.e. textual reviews), we can understand patients opinions [15] (i.e. Positive, negative or neutral), emotions (i.e. sad, anxiety) [33] and demands, by means of sentiment analysis. In our study, patients online WOM are written as textual content, therefore, the text analysis method plays an essential role in mining the characteristics of the textual WOM. In this way, we are able to analyze the patients' attitude, needs and motivations.

3. Research context

3.1. Dataset

3.1.1. Online health consultation website background. Like other OHCs website, Guahao.com provide health information inquiry, health consultation and online appointment services. Physicians are divided into specific board based on their departments or forte or hospital. Patients could explore information about the physicians through checking description information provided by themselves, or by referring to other patients WOM.

3.1.2. Data collection and preprocessing. To obtain the secondary data, we set up Java WebCrawler which started on March 8th,2018 to crawl patients' reviews, the crawler lasted for two days. We obtain 384,650 reviews for 3,588 physicians, with an average of roughly 107 reviews per physician. Raw corpus are made of long sentences with the combination of words, some also including nonsensical symbols, punctuations, numbers and stop words. These meaningless elements are called as noise and will increase the difficulty of text analysis and influence the analysis accuracy, for example, the stop words like "is" and "the" will occupy most of the frequency thus reducing the real frequency of special words. To address this issue, a preprocess procedure is conduct for all reviews before further analysis. As is shown in Figure 1. The preprocessing procedure followed by data crawling and storing, contains segmentation and filtering (to remove stop words, numbers and punctuation).

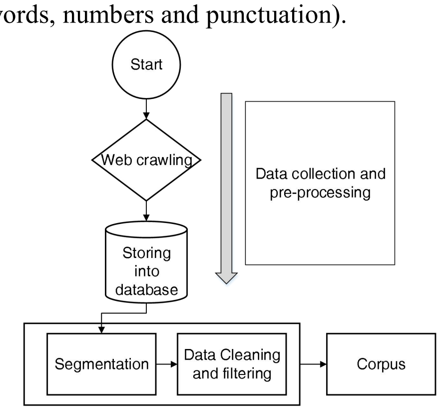

Figure 1. Data collection and pre-processing

3.2. Bigrams frequency analysis

Though count the term frequency in a document, we are able to make a good sense of the main concerning of the publisher. Accordingly, we utilize the widespread used TF and TF-IDF methods to calculate the important referring in patients WOM.

3.2.1. TF Frequency. For given text documents, the number of times a term occurs in a document is called its term frequency. In general, term frequency refers to the most relevant information included in the document. Given a document d, the term frequency of term *t*, *tf(t,d)* is defined as follows:

$$tf(t,d) = f_{t,d}$$

Where $f_{t,d}$ equals the number of times that term t appears in document *d*. For document set *D*, the total frequency of term *t*, is defined as:

$$tf(t,D) = \sum_{d=1}^{D} f_{t,d}$$

Where *d* is an individual document in *D*.

3.2.2. Term Frequency-Inverse Document Frequency (TF-IDF). In the case of using raw count of a term as the term frequency could tend to incorrectly emphasize some common words more frequently, for example, the word '*physician*' may occur in most of the patients' reviews. However, this term delivers limited discriminative information, without giving enough weight to the more meaningful terms.

Therefore, an inverse document frequency factor is introduced which diminishes the weight of terms that occur very frequently in the document set and increases the weight of terms that rarely occur [39]. Actually, TF-IDF count term frequency through determining the relative frequency of words in a specific document compared to the inverse percentage of that word over the entire document set [46]. Given a document d, which included in document set D, the TF-IDF of term t can be calculated as follows:

$$\text{tfidf}(t,d,D) = tf(t,d) \times idf(t,D)$$

3.3. Lexicon-Based sentiment analysis

The lexicon-based approach generally relies on a series of standard dictionaries such as LIWC to map words within corpus and compute its sentiment or determine the sentiment polarity [11]. Table 1 summarize dictionaries used in this paper. Those standard dictionaries contain sentiment words (i.e. positive words and negative words) dictionary, degree words dictionary (i.e. very, most) and negative words dictionary (i.e. not, no).

As shown in Figure 3, the documents would be segmented into pieces, then stop words, punctuation and numbers would be removed. It is a necessary procedure to filter noisy terms. Finally, to do sentiment analysis, the 'clean' corpus would be mapped with each standard dictionary. For the corpus *C*, its sentiment can be computed as follows:

$$sentiment(C) = \sum_{w=1}^{W} (-1)^{p} \times d \times S_w$$

Where *W* denotes the number of clauses in corpus and *w* is a single clause, S_w denotes the original standard sentiment score of the keyword in *w*, *p* represents the number of negative words that embellish *w*, and *d* appends the sentiment degree of S_w according to the degree word dictionary. Exclusively, if *p* is odd, the sentiment of *w* would be inverted.

Table 1. Standard sentiment dictionary

Category	example
Ontology dictionary	surgery, treatment, cardiopathy, diabetes
Sentiment dictionary	negative: bad, terrible, dislike
	positive: good, like, professional
Degree word dictionary	most degree, very degree, more degree, general degree, least degree
Privative word dictionary	no, not, none

3.4. Feature words analysis

In the present work, we employed a text analysis program called TextMind to cluster feature words in patients' reviews. TextMind is a Chinese language psychological analysis system developed by Computational Cyber-Psychology Lab, Institute of Psychology, Chinese Academy of Sciences. TextMind provides easy access to analysis of the preferences and degrees of different categories in a text. Inspired by the dictionary of LIWC2007 and C-LIWC, TextMind is developed based on the characteristics of Simplified Chinese language in mainland China [14]. The clustered words categories could reveal the user's attention focus, thinking styles and individual differences in language use.

3.5. Topic model analysis

Topics generally refer to the hidden structure in an article, blogs or review. Topic models are algorithms developed for discovering the focal hidden themes that pervade a huge and other unstructured collection of documents [4]. In this paper, we use latent Dirichlet allocation (LDA) [5] to mining topics in patient reviews. As one of the most elementary topic models, LDA has been widely used in topic mining and text clustering. For each document *w* in a corpus *D,* the

LDA process can be described as:

(1) Select N words from w, where $N \sim Poisson(\xi)$;

(2) Select θ, where $\theta \sim Dir(\alpha)$;

(3) For each of the N words w_n:

Select a topic $z_n \sim Mutinomial(\theta)$;

Select a word w_n from $p(w_n \mid z_n, \beta)$, a multinomial probability conditioned on the topic z_n.

The algorithm mechanism can be defined as the following graph:

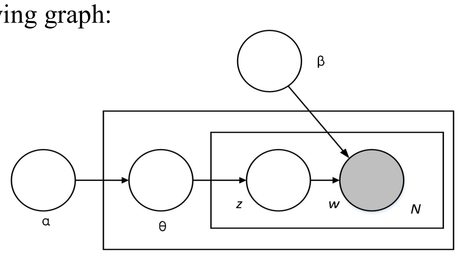

Figure 2. Graphical model representation of LDA

Posterior computation is a crucial issue of topic modelling. Generally, there are two kinds of computational approaches: sampling-based algorithms and variational algorithms. In our present work, We introduce Gibbs sampling [16] schemes to speed up the parameter estimation. Choosing the proper number of topics is another problem in topic discovery. To deal with this problem, we set up an iterated modelling method, we set a range of topic numbers *K*= {5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100}, for each k in K, there will be a ten-fold training procedure. Then we could obtain a perplexity index and a log-likelihood index for each fold. The perplexity is a conventional index to evaluate the performance in language modelling, is monotonically decreasing in the likelihood of the test data, and is known as the exponential of the average negative log-likelihood [3]. A lower perplexity score indicates better generalization performance. Oppositely, A higher likelihood score suggests better modelling ability.

4. Research results

4.1. Descriptive statistics analysis

Through web crawling, we finally obtain 384,650 reviews for 3,588 doctors. Those reviews were posted between June, 14th 2012 and March, 9th 2018. Figure 5 shows that there was a moderate increasing from 2012 to 2015, while a sharp upward tendency occurs in 2016.

To our knowledge, Guahao.com accomplished its biggest financing on September, 2015, from then on, it made massive progress in the Internet healthcare industry and attracted more and more users, including patients and physicians joining in Guahao.com.

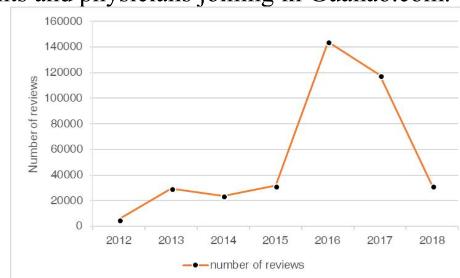

Figure 3. Number of reviews from 2012-2018

From Table 2, we can find that some physicians got more reviews than others, for a reason is that those physicians may provide higher quality services or hold better reputation, thus attract more patients.

Table 2. Number of reviews of physicians

Number of reviews	Number of physicians
<10	453
10~50	1543
50-100	584
100-200	422
200-500	364
≥500	222

For further statistical analysis, as shown in Figure 4, patients usually wrote reviews between 9:00 am and 19:00 pm. Interestingly, there was a peak at 20:00 pm. It could be a signal that people are usually free during this time, and care more about health issue than any other period.

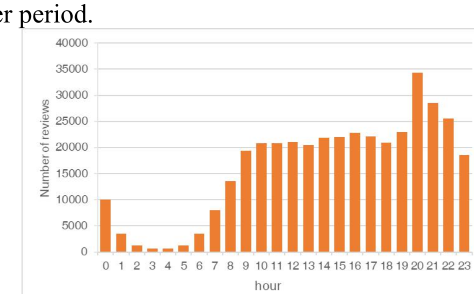

Figure 4. Number of reviews on different hours

4.2. Text analysis results

4.2.1. Frequent bigrams distribution. Figure 5 indicates the top 20 frequent terms in patients' reviews calculated by TF. Terms such as '*physician*', '*thanks*' and '*patient*' show literally high occurrence rate. It is because that most of the reviews contain these words. As discussed in part 3.2, TF uses raw count of terms as frequency. Hence it is not helpful to find discriminative terms. As a consequence, we recompute the term frequency using TF-IDF.

As displayed in Table 3, the most frequent words changed and some special terms arisen, for example, '*environment*', '*surgery*' and '*appointment*', these words may not be very frequent in the whole document set, but they capture discriminative information of the review. Through these words, we can find patients' focus attention, in other words, what the patient care about and what they want. Also, we can find that some terms may relate to patients compliant, for example, *'wait*' and '*sad*', patients would express their dissatisfaction about long waiting time and disappointing service quality through reviews. Hopefully, it will be helpful for other potential patients to adjust their consultation decision.

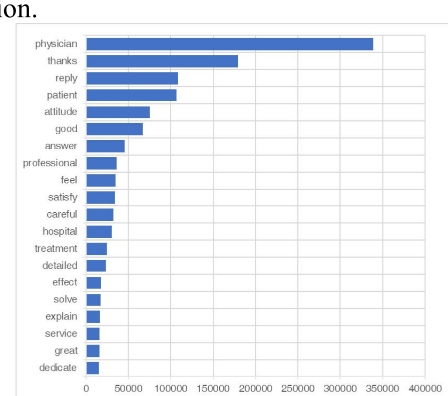

Figure 5. TF frequency of terms

Table 3. TF-IDF frequency of terms

TF-IDF Frequency	Terms
20000-30000	reply, environment, treatment, effect
15000-20000	feel, answer, hospital, patient, time, wait, surgery, professor
13000-15000	sad, appreciate, check, app, appointment, flexible
12000-13000	great, solve, thanks, mood, photo, mobile
11000-12000	question, record, Chinese-herb, therapy, simple
10000-11000	attitude, detail, careful, revisit, condition, explain

4.2.2. Sentiment distribution. Figure 6(a), (b) and (c) display negative review rate, neutral review rate and positive review rate of 3,588 physicians. It is evident that positive reviews occupy the most proportion of reviews. The percentage of negative reviews mainly lie between 10%-15%, the percentage of neutral reviews shows a similar distribution.

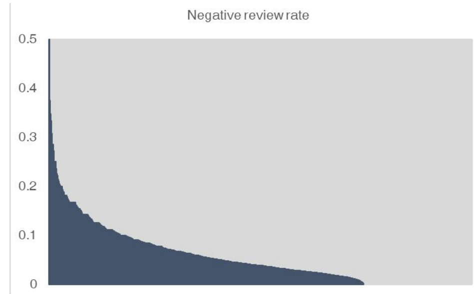

Figure 6(a). Negative review rate for each doctor

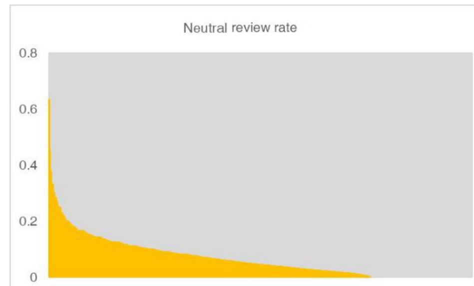

Figure 6(b). Neutral review rate for each doctor

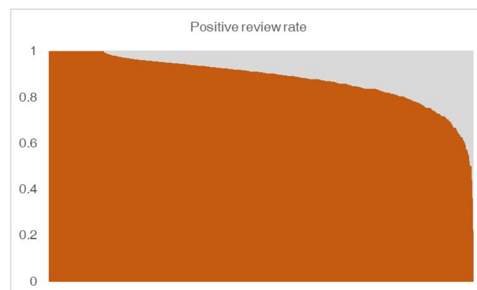

Figure 6(c). Positive review rate for each doctor

According to Figure 6(d), we find that the average sentiment score of per review of each physician mainly lies between +2 and +4. It indicates that most of the reviews are written in a placid mood, in other words, only a few patients put lots of emotional expressions into the review.

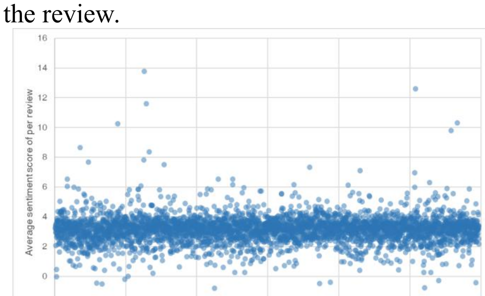

Figure 6(d). Average Sentiment score of reviews for each doctor

However, it should not be ignored that there are still some precisely negative reviews, which implicitly contain notable information represent that the service and website quality, doctor's literacy need to be improved. According to prior research, compared to positive information, negative information may have a significant impact on evaluations [19]. Studies also find that negative reviews tend to play a more meaningful role or serve as a reminder signal in the marketplace [8]. For further discussion, we have some samples in table 4 to illustrate what makes patients dissatisfied.

Table 4. Samples of negative reviews

(1) Impatient! Bad attitude! Let me wait for so long but didn't reply!
(2) Received my money but did not deal with my consultation. No medical ethics!
(3) The doctor is totally irresponsible and the price is very high. I am not satisfied with his answer.
(4) The treatment plan is absolutely incorrect. It's so terrible.
(5) The description of the function is vague, too troublesome to initiate a consultation.

From Table 4, it is noted that patients would make complaints about waiting time, doctors' attitude as well as service quality and the function vulnerability of the website or mobile applications. Most of the negative reviews carry quite strong emotions, i.e. anger or disappointed. These reviews could be an alert for potential users of the service, remind them of possible loss of money and time. Meanwhile, it can be useful clue represent users' requirements, thus help the manager of the online health community as well as website developers to renovate their functionality and marketing strategy.

4.2.3. Feature words distribution. Figure 7 displays the clustering result of feature words within patient reviews.

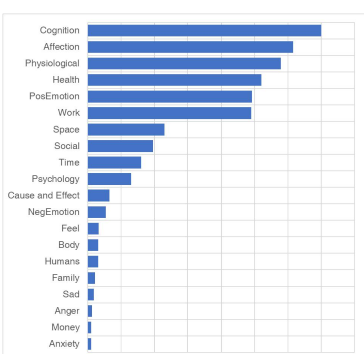

Figure 7. Feature words distribution

As we can see, the most frequent feature set is the words represent people's *cognition*, *affection* and *physiological index*. It is easy to understand this phenomenon since these reviews come from healthcare (or medical) fields. Users in online health communities tend to mention their *health* conditions, *emotions* and *feeling* because it can be a release of stress and anxiety [38], which is brought by poor health situations and pain of disease. Apart from that, words referring to *work* and *social* life are often mentioned, it is probably because people usually relate their health issue with work load and daily experience [47].

4.3. Topic model result

Through running the topic modelling algorithm, we obtain a series of perplexity index and likelihood index which represent the modelling performance under different topic numbers. According to Figure 8 and Figure 9, it is apparent that the most appropriate topic number approximate 50. As a consequence, we launched LDA with a topic number of 50. Then, each corpus is assigned to one or more topic, for illustration, we select five topics and exhibit the most frequently occurring words in each topic in Table 5.

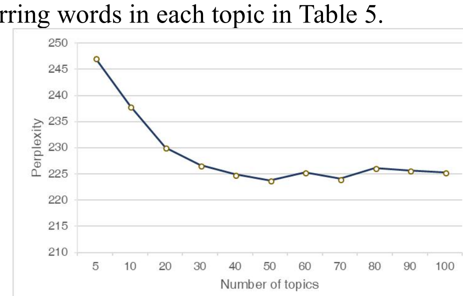

Figure 8. Perplexity trend of LDA

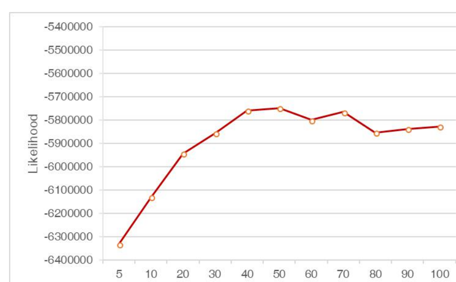

Figure 9. Likelihood trend of LDA

The name of each topic was determined according to the following strategies. First, referring to domain ontology, we group entities describe the same medical case, for example, '*heart*' and '*surgery*' would stand for the cardiac topic. Second, words with similar meaning or used to the relevant process were utilized for topic identification. For example, '*register*', '*appointment*' and '*check*' account for the procedure that a patient uses e-Health service. Last, we decide the name of a topic based on the characteristic or property of a certain word. For example, '*careful*', '*professional*' and '*excellent*' are usually used to describe the service quality of a doctor.

From Tables 5, we can directly see the apparent distinctiveness of several topics. Topic 1-3 are topics related to medication case while topic 4 represent service-related items. As for topic 5, it is noted as measures about a physician, for example, physician's service quality and medical literacy. The topic modelling result provide cue about patients' main focus or motivations when using online health consultation.

Table 5. Top 10 words and topic names of selected topic

Topic 1: cardiopathy	Topic 2: children got a flu	Topic 3: eye disease	Topic 4: online health service	Topic 5: service and attitude of doctor
patient	cough	child	check	responsible
blood pressure	child	eyesight	attitude	leechcraft
heart	baby	diagnosis	appointment	enthusiastic
illness	asthma	shortsightedness	register	excellent
symptom	kid	eye	hospital	kind
care	flue	check	queue	attitude
stent	allergy	astigmatism	expert	perspective
diagnosis	diagnosis	glasses	professional	professional
re-diagnosis	medicine	headache	responsible	careful
electrocardiogram	pneumonia	patient	re-visit	quality

5. Discussions and conclusions

There have been many studies investigating the IT-Enabled health service. Previous research shows that the IT-Enabled collaborative technology plays an important role in enhancing the health service delivery , providing medical support and facilitate the collaboration among caregivers and health consumers [13]. However, few studies explored users' attitude to the ICT assisted health service. Our study filled this research gap through a case study analyzing user reviews posted on online health consultation website, via text analysis methods. Specifically, we leverage four natural language processing techniques, term frequency analysis, sentiment analysis, feature words clustering and topic modelling to explore how patients express their opinions on health services quality, physicians' attitude and website functionality. Our research further verified the popularity of IT-Enabled health service and provide a comprehensive interpretation of patients' WOM on online health consultation.

Overall, our analysis reveals some patterns of WOM on online health consultation: (1) From the results of the descriptive analysis, we can conclude that the IT-Enabled health service is experiencing an increased tendency as confirmed in other research [43]. (2) The results of the term frequency analysis show that while patients' concerns on IT-Enabled health service vary from doctors, website function, emotional support and the physician-patient relationship, the emphasis lies in service quality and benefit acquisition. (3) Sentiment analysis results show that most of the reviews carry a mild positive sentiment. Scarcely were reviews filled with extreme strong emotionality. This phenomenon is consistent in other IT-Enabled collaboration platforms [35]. In other words, most of the physicians seem reliable and responsible when providing online healthcare services. (4) We make conclusion from the result of the feature words clustering, that patients tend to mention their health conditions, social experience and emotions in WOM. It can be interpreted that health issue is usually related to individual's social environment and emotional status [47]. (5) Topic modelling results indicate that users are mostly concerned with physicians' medical skills and their attitude. As is refereed in previous research, patients are usually desired to be respected and supported by the doctor, apart from obtaining valuable services [22]. These findings are directions for the establishment and maintenance of the physician-patient relationship.

Concentrating on IT-Enabled collaborative health service, our research shows that present online health services are not good enough to satisfy public demands. As shown in sentiment analysis and topic modelling, many users may feel disappointed by unqualified service and unfair pricing. Despite the urgent needs of healthcare services delivered by ICT, the maturity of this industry is far from public expectations.

6. Implications and future directions

Our research results have both theoretical and practical implications in the construction of better collaboration in IT-Enabled healthcare service. First, our research extends the theoretical context in understanding the IT-Enabled health service from the perspective of users. Textual patterns contained in patients' reviews confirmed above assumptions and specifically shed light on how to better understand patients, enhance the quality of e-Health service and increase patient satisfaction during online health consultation. Through the emotional analysis of the posts in the forum, we can understand the emotional need of the OHC members. Second, our research provides numerous practical implications for implementing IT-Enabled collaboration project in healthcare service. For example, websites developers are supposed to optimize the user-interface and modify vulnerability. Doctors are suggested to establish an equal and relaxed relationship with patients, although sometimes there are a lot of orders waiting to be processed. More importantly, doctors should be aware of their responsibility for patients and be careful about each treatment. The manager of these website should check out their pricing and marketing strategies, take the responsibilities to figure out wrong information or fake information and make strict regulations to supervise the caregivers.

The current study also has several limitations that could be addressed in future research. First, the data we used are from only one online health community. It will be more persuasive if take more websites into account. Second, quantitative research checking the relationship between patients reviews and doctors' orders would deepen our comprehension of the impact of patient WOM. We are prepared to do further investigation on Internet healthcare industry.

7. References

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