Original Paper

Hai-Yan Yu¹,²,³, PhD; Jying-Nan Wang¹, PhD; Ya-Ling Chiu¹, PhD; Hang Qiu²,⁴, PhD; Ling Xiao¹, PhD

¹School of Economics and Management, Chongqing University of Posts and Telecommunications, Chongqing, China
²Big Data Research Center, University of Electronic Science and Technology of China, Chengdu, China
³Department of Statistics, The Pennsylvania State University, University Park, USA
⁴School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China

Corresponding Author:
Ling Xiao, PhD
School of Economics and Management
Chongqing University of Posts and Telecommunications
No.2 Chongwen Rd, Nan’an District,
Chongqing, 400065
China
Phone: 18716283872
Fax:
Email: xiaoling5231@163.com
Impact of Patient Crowdvotes Aggregated Service Diversity on Doctors’ Service Sales in Online Health Community: a Retrospective Study

Abstract

Background: An increasing number of people visit online health communities to enquire health information with doctors. In the online health community (OHC), patient crowds tended to label and vote the doctors’ specialties with encountered disease. Understanding how patients’ online labels can help us understand the service diversity for patients in online health communities and provide constructive suggestions for doctors serving more patients online.

Objective: Our goal was to understand: (1) what kind of patterns are the labels of patient crowdvotes aggregated service diversity, including encountered disease labels and online votes, in a OHC? (2) whether the patient crowdvotes aggregated service diversity make doctors’ service sales difference in OHC? (3) how can managers in OHC perform to improve doctors’ service sales with the feedback of crowdvotes aggregated service diversity?

Methods: We designed a retrospective study with data collected from the largest OHC (Good Doctor website) in China. We first used descriptive statistics to investigate the patient crowdvotes aggregated service diversity. Then a multiple log-linear relationship was adapted to investigate the main and the interaction impact of service diversity on doctors’ service sales.

Results: Our sample consists of 9,841 doctors from 1,255 different hospitals widely distributed in China. 18,997,018 patients had been serviced by these doctors since they became members of the study OHC. 704,467 votes of doctors’ clinical specialties were labeled by patient crowds in recent two years (Aug.26, 2015-Aug. 25, 2017). Gini coefficient of serviced patients is very high, 0.626, followed by the volume of votes (0.562). Based on the regression model, we found that the coefficients of the control variables, doctor review rating and clinic title, were 0.810(0.041), and 1.735 (0.027), respectively. For the breadth of voted specialties, volume of votes and degree of voted diversity, the standardized coefficient of the main effect were 0.309 (0.038), 0.745 (0.014) and 0.073 (0.018), respectively. All of the estimates are statistically significant at a 0.1% level.

Conclusions: Our study provided empirical evidence that the patterns of both the labels of patient crowdvotes aggregated service diversity and doctors’ service sales were of inequality (as illustrated in Lorenz curves) in the distribution of its size of serviced patients in a OHC. Patient crowds’ online labels also leaded to differences in the doctors’ service sales online. The treads of the doctors’ service sales kept increasing as the patient crowdvotes aggregated service diversity increased. Finally, our findings suggested that the higher breadth of voted specialties and degree of voted diversity displayed a greater service sales with a higher review rating, deploying less inequality of Doctors’ service sales.

Keywords: online health community; service diversity; crowdvotes aggregating; Lorenz curve, interaction effects.
Introduction

Background

As an increasing number of people visit online health communities (OHCs) to consult health problems with doctors, this phenomenon has been receiving great attention of many researchers[1,2,3,4]. Among the studies on OHC, various issues were taken into account, such as whether websites can be effectively shared by patients in online health communities [1, 2]; can rural-urban health disparities be reduced in an online health community [3]; and how did doctor online material and physiological rewards can impact the doctors' online contributions in OHC [4]. In China, such kind of OHC platforms dominated by government or entity hospitals provide much-needed health services for more and more people, especially those with leg problems or living in grass-roots remote areas. Moreover, benefiting from the growing accessibility and bandwidths of Internet in China, its internet medicine market had maintained a compound annual growth rate of 31.1% since 2014, at which time the market size was valued at 11.4 billion yuan (RMB)[5]. Although certain incidents exposed the weakness and risks of online medical consultation service, many stakeholders realized that such service in OHC was a useful supplement rather than a replacement of the diagnosis and treatment to the entity hospitals. Therefore, this type of service is expected to increase in OHC, providing convinces for the existing and potential patients, doctors, and hospitals.

In online health community (OHC), it is not just a platform for doctor-patient communication, but also a site for the patient crowds to aggregate their information of medical experience. Since committed members of OHC have reasons to remain active, the patient crowds would feel the need to contribute. In particular, patient crowds tended to label doctors’ specialties with their encountered disease and give their votes online. There have been many companies offering this type of service, among which the Good Doctor website is a typical example [4]. The Good Doctor website (www.haodf.com) started in 2006, is the earliest online doctor review website in operation in China. Due to the national promotion of “internet+” program and the improvement of internet accessibility in healthcare area, a large number of doctors were encouraged to provide online medical service appropriately, and importantly, an increasing amount of patients would like to choose a virtual medical consultation service on OHC. According to the Good Doctor website, it recruited 480,000 doctors (nearly 29.583% of them with actual verified identities) from 7,216 hospitals at the end of year 2016. Meanwhile, about 40,737,197 patients succeeded in evolving in online medical consultation. Notably, they were distinctly counted for the same doctor but possibly repeatedly counted for different doctors. One key factor of OHC’s success is whether a patient could find the right doctor with the required specialties to take the online medical consultation service. Moreover, doctors specializing in gynecology/obstetrics has the largest average numbers of reviews in China[6], and one observational evidence suggested that the physicians in the gynecology/obstetrics were considered to be more people-oriented and compassionate compared with other specialties [4], which also caused the doctors to be more involved with the OHC to help more patients.

However, demonstration of specialties in their personal introduction of doctors are somehow difficult or unclear to understand for the patients. While patient crowds tend to label and vote the doctors’ specialties with encountered disease, understanding how patient crowdvotes aggregated service diversity impact on doctors’ service sales is a critical issue for the OHC study. This paper designed a retrospective study to investigate this argument with the observational data in Good Doctor website.

Research Problems
The importance of patient crowds’ online labels (or posts) for sharing their medical experience in OHC has been verified by extensive research [1,2,3]. Establishing an effective information cascade mechanism is one of the most common ways to maintain community crowds’ wisdom [7,8,9]. Despite the fact that OHC of practice has been in existence around the world over a decade, very little is known about information cascade mechanism that could foster patient crowds’ wisdom to contribute and capture the patterns of doctors’ specificities in the OHC. The OHC managers can establish information cascade mechanisms, such as labels of doctors’ specialties abstracted from encountered disease and their online votes, while the conventional research on information aggregating mechanisms of online voting labels suggested that the online service were unavoidable to be of inequality in distribution of service sales [10]. Other empirical experience suggested that for the patients with voting information, they could find the right doctor with the specialties much easier than just reading the doctors’ induction of their specialties. Therefore, we examined whether the patterns of doctor online service sales is affected by patient crowdvotes aggregated service diversity in this study. Our motivation is to investigate the following three issues:

1. what kind of patterns are the labels of patient crowdvotes aggregated service diversity, including encountered disease labels and online votes, in a OHC?
2. whether the patient crowdvotes aggregated service diversity make doctors’ service sales difference in OHC?
3. how can managers in OHC perform to improve doctors’ service sales with the feedback of crowdvotes aggregated service diversity?

**Methods**

**Research Models**

The study is designed as a retrospective observational study. The research framework was demonstrated in Figure 1. First, the doctor online service—amount of served patients— is formulated as the dependent variable, which is a stock variable. Second, the service diversity (patient crowdvotes aggregating information) —breadth of voted doctors’ specialties, volume of total votes and degree of votes diversity— are considered as the dependent variables of service diversity in OHC. The first two are also stock variables and the third one is a new defined continuous variable. Finally, control variables—doctor review rating and clinic title—represent the doctor’s status at a specific time. With this framework, we can reveal the patterns of the doctors’ online service and the correlational relationship between patient crowdvotes aggregated service diversity on doctors’ service sales.

<table>
<thead>
<tr>
<th>Service Diversity (Patient Crowdvotes Aggregating)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Breadth of voted Specialties (Doctors’)</td>
</tr>
<tr>
<td>2. Volume of Votes</td>
</tr>
<tr>
<td>3. Degree of Votes Diversity</td>
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<th>Doctors’ Service Sales</th>
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<td>Amount of Served Patients</td>
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<th>Control Variables</th>
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<tr>
<td>1. Doctor Review Rating</td>
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<tr>
<td>2. Clinic Title</td>
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</table>

Figure 1. The framework of the study of the effects of patient crowdvotes aggregated service diversity on doctors’ service sales in a OHC.
Crowd voting occurs when a website gathers a large group's judgments or opinions on a certain topic [11]. The voting system is one common category of crowdsourcing effectively implemented in the commercial industry [7, 12]. To achieve a cumulative result, the system provides a sourcing model in which individuals or organizations obtain goods or services from a large and relatively open group of online users (often rapidly-evolving) [13]. Through dividing work among participants, advantages of using crowd voting may include improved flexibility, scalability, quality, speed, costs, or diversity. In OHC, patient and clinician online contribution and engagement [1, 14] were investigated in researches of word of mouth [15] and experience sharing[16]. But the application of text mining [17] or content analysis of comments (poster mining) [18] in OHC has too many terms which make the acquired knowledge fuzzy and difficult to understand. Despite of large amounts of homogeneous contributions, crowd voting systems seek a collective value emerging only from the quantitative properties of the collection of distributed work. On a given topic, contributions represent votes in OHC. Since the labels annotated by the users are inherently subjective for a lot of online tasks, substantial variation could not be avoided among different annotators [19]. To accurately deduce a collective response, these systems aggregated a sufficient number of these votes which reflected the wisdom of crowds [20]. Meanwhile, some systems of crowd voting provide channels for organizations to learn beyond the base of minds from their own employees. For example, users collectively vote or rate the contents on the webs of reddit and AskScienceconline. The crowd voting techniques were also emerging in the researches of public health [21,22,23]. Through this technique, researchers can move from small homogeneous population of participants to large heterogenous population with diverse backgrounds, which could also be expected to be unbiased. Moreover, minimax entropy [24] was implemented to deal with crowds noise [25] in multiple votes by each voters, even arriving at true collective judgments [26]. However, most of the crowd voting systems are evolved by people who directly or indirectly benefit from its outcome. In the incentive mechanism, motivations for contributing to online communities were mainly classified in three categories [27]: sense of efficacy, increased recognition and anticipated reciprocity. Although researches provided measures to evaluate the performance of crowd sourcing systems[28], how they impact the service performance (in particular doctors’ serviced sales in OHC) is still deserving more investigation.

Measure of diversity (or concentration) was first introduced by Yule [29,30] and achieved when the individuals of a population were classified into groups. On industrial diversity [31], however measured, it typically has been used as a proxy which describes the extent to which the structure, and consequently the conduct and performance, of an industry approximates competition or even monopoly conditions. On service productivity, many recent studies investigated online service diversity in other kinds of online communities such as Amazon and Uber [32]. The diversity of drivers’ service destination were reported to enrich the variance of their earnings, resulting in the reserve selection of drivers’ service. To gain service productivity, service diversity played different roles from both supply side and demand side [33].In health service, digitally enabled tele-healthcare service innovations had been claimed to have the capacity of bridging the service divide between medical needs and supply[34]. The delivered service could reach new patient groups through new mode, even though the service might not be new. Moreover, recommendation on online commerce is one important function which improves sales diversity. One traditional argument suggested that recommenders helped consumers discover new products and thus increased sales diversity. The effect of recommender systems was also been examined on the diversity of sales, fighting with the argument that recommenders only reinforce the popularity of already-popular products. The recent research [10] suggested that a reduction in sales diversity could be brought out by some
well-known recommenders, which recommend products based on voting, sales and other related historical data (even limited). Although these recommenders can enhance a rich-get-richer effect for popular products and vice versa for unpopular ones, this bias toward popularity will prevent what may otherwise be better consumer-service matches, especially in online medical consultation service. Despite of those recent progress in the diversity of product sales, few studies considered the impact of customers’ voting service diversity on providers’ service sales in OHC.

Data Collection

Through web crawler, the retrospective observational data were collected from the Good Doctor website where more than 142,448 doctors’ profiles were deployed. However, only after a doctor applies for a personal web page is he/she able to provide full online services, e.g., online dialogue with patients or the sharing of professional articles. The labels of doctors’ specialties and their votes were collected over two days (as the duration of data collection was from August 26, 2017 to August 27, 2017). The number of patient crowd votes in the profile for a physician ranged from one to 1723. The average number of all patient votes to each physician was approximately 8 labels with a standard variance of around 32. To make the data source are reliable and stable for analysis, the inclusion and exclusion criterion was based on:

(a) Volume of votes of doctors’ specialties needs to be no less than a cut-off (i.e. 5 for keeping the number of past serviced patients is not zero), remaining the effective identification and removal of bias from the crowd’s wisdom, and the design of systems that minimizes such bias. Previous findings\cite{35} suggested that one-off voters tend to vote on popular items, meaning that one-off votes could not represent the service diversity.

(b) Service labels were voted during the last two years, namely from July 27, 2015 to July 26, 2017. The number of past serviced patients is no less than one, and the mean of the overall ratings in user reviews of doctor $i$ is no less than one.

Thus, the 140,344 doctors with personal web pages on the site were considered for the purposes of the study to be genuinely involved in the website, and others were not included in our sample. From the original data set, 9,841 samples of doctors were remained after filtering. The total vote amount of all doctors’ specialties is 704,467 and that of serviced patients is 18,997,018. Thus, we designed a retrospective study involving a data sample collected as shown in Figure 2. The collected data included the doctor’s ID (personal web site) along with the labels and votes (by patients) on doctors’ specificity, and the number of serviced patients.
Characteristics of the samples are worth noting in the following aspects. First, the patient crowd votes is different from the doctors’ review votes for the word-of-mouth rating, and it is also different from the records of doctors’ accumulated clinical experience. Patient crowd votes represent their contributions on sharing medical experience. Although those votes and the labels of physicians’ specialties were provided with inherently subjective information, their advantage lie in that more labels familiar to physicians were given and much each to understand for other patient in the OHC. Second, the amount of the patients are those patients serviced during the investigating time, not including those visited the patients who had visited the doctor before, in particular, multiple times of visits are also recorded in only one time. Third, the 9,841 doctors came from 1,255 different hospitals widely distributed in China. The clinic titles were categorized into five classes, including (from junior to senior) chief doctor, associate chief doctor, attending doctor, resident doctor, and others. Moreover, we also collected the doctors’ review ratings (also regarded as online word-of-mouth), with mean value equaling to 2.746 on a scale from 1 to 5 and 5 being the highest score.

Measures

Before examining OHC platform’s effects, it is necessary to distinguish between sales and service diversity. Service diversity typically measures how many different specialty labels (of services) a doctor offers. It is a supply-side measure of breadth. In contrast, we use sales diversity to describe the concentration of online medical service market shares conditional on doctors’ consultation service.

Measure of Doctor Service Sales

This study on total amount of doctor i’s past served patients online will provide evidence to factors of success on which the potential customers select an online doctor and reveal the
evolving mechanism of clinical acceptance of telemedicine. SP$_1$ is measured as the cumulative size of the served patients (referring to the sales of doctors’ service) in the past.

The dependent variable will be used to reveal the patterns (i.e., inequality phenomena) of the doctors’ online service and the relationship between patient crowdvotes aggregated service diversity on doctors’ service sales. The distribution of the online patient virtual visits across the physicians in OHC was characterized by a Lorenz curve in which the cumulative proportion of online patient virtual visits was plotted against the cumulative proportion of physicians in the OHC.

**Measure of Crowd Votes Aggregating**

To reduce the bias of the crowd’s wisdom, we provide three measures on the crowd votes, including breadth of voted specialties, volume of votes and degree of voted diversity.

Given the voting states($S_i$, # Votes($S_i$)), $S_i = \{s_{i1}, s_{i2}, ..., s_{im}\}$ is the vector of doctor $i$’s service specialty labelled by the serviced patients, and # Votes($S_i$) is the corresponding volume vector of their votes.

(a) Breadth of voted specialties

The total amount of doctor $i$’s service specialties labelled by the serviced patients

$$BS_i = \sum_{j=1}^{m} I(# \text{Votes}(S_j)>0)$$  

(b) Volume of votes

The total amount of doctor $i$’s votes given by the serviced patients

$$VV_i = \sum_{j=1}^{m} # \text{Votes}(S_j)$$

(c) Degree of voted diversity

Measure of diversity or concentration was first introduced by Yule $^{29}$ and achieved when the individuals of a population were classified into groups. The degree of diversity was defined as statistics to be calculated from sample data.

Entropy is one of several ways to measure diversity. Information entropy is defined as the average amount of information produced by a stochastic source of data$^{[36]}$. Roe MT et al. $^{[37]}$ studied the association of specialty care with the treatment of patients. Due to the independent sources, information entropy was adapted to measure the diversity of doctors’ service specialty in the logarithm of the probability distribution (label board votes).

The probability vector is represented as

$$P(S_i) = \{P(S_{i1}), P(S_{i2}), ..., P(S_{im})\},$$

where $P(S_{ij}) = \frac{# \text{Votes}(S_{ij})}{\sum_{j=1}^{m} # \text{Votes}(S_{ij})}$ is the probability of the service specialty $S_{ij}$, and # Votes($S_{ij}$) is volume of the doctor $i$’s $j$th service specialty.

Based on the theory of information entropy, the diversity of doctors’ service specialty is measured as,

$$DD_i = \text{Entropy}(S_i) = -\sum_{j=1}^{m} P(S_{ij})\log_2 P(S_{ij})$$

where $P(S_{ij})$ is the probability of the service specialty $S_{ij}$.

Since observation of less probable events occurs more rarely, the net effect is that the entropy (thought of as average information) received from non-uniformly distributed data is always less than or equal to $\log_2(n)$. Entropy is zero when one outcome is certain to occur. Entropy only takes into account the probability of observing a specific event, so the information it encapsulates is information about the underlying probability distribution, not the meaning of the events themselves.

**Control Variables**

As our previous study did, a few of control variables can be introduced into OHC study. To focus on the service diversity, herein we employ two control variables. A continuous variable of the mean of the overall ratings in user reviews of the doctor ($DR_i$) and the categorical variable of the codes of the clinic titles ($CT_i$) as control variables are adapted as the control variables$^{1}$. 

In this study, all control variables are stock variables, which represent the online and offline status of doctors at the data acquisition time. The definitions and measurements of all variables are demonstrated in Table 1.

Table 1. Variable definitions and measurements

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
<th>Measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SP_i$</td>
<td>Size of serviced patients</td>
<td>The total amount of doctor $i$’s serviced patients, indicating doctor $i$’s service sales online</td>
</tr>
<tr>
<td>$BS_i$</td>
<td>Breadth of voted specialties</td>
<td>The amount of doctor $i$’s service specialties labelled by serviced patients (encountered disease labels)</td>
</tr>
<tr>
<td>$VV_i$</td>
<td>Volume of votes</td>
<td>The amount of doctor $i$’s votes given by the serviced patients (online votes)</td>
</tr>
<tr>
<td>$DD_i$</td>
<td>Degree of voted diversity</td>
<td>Information entropy of doctor $i$’s service specialty (labeled and voted by patients) in the logarithm of the probability distribution.</td>
</tr>
<tr>
<td>$RR_i$</td>
<td>Review rating</td>
<td>Mean of the overall ratings in user reviews of the doctor $i$ (scoring from 1 to 5 with 5 being the highest score).</td>
</tr>
<tr>
<td>$CT_i$</td>
<td>Clinic title</td>
<td>Codes of the clinic titles, including chief doctor, associate chief doctor, attending doctor, resident doctor and the others as 5, 4, 3, 2, 1.</td>
</tr>
</tbody>
</table>

To interpret the coefficients as percentage changes, we used logarithmic transformations of the variables (except $DD_i$), because the empirical distributions of the transformed variables are more suitable for ordinary least-squares regression. Thus, $\ln(\cdot)$ are the logarithmic transformations of these variables. Meanwhile, to identify the interaction effect of those covariates, we further transferred the variables into dummy variables $Bin(\cdot)$ with binary transformations. For example, $Bin(RR_i)$ is the binary transformation of $RR_i$ with 1 indicating review ratings no less than its median and 0 indicating review ratings less than its median.

**Statistical Analysis**

To test the main conjecture of whether doctors’ patient crowd votes will affect doctors’ service sales, we first fit the size of serviced patients and volume of votes data for the individual doctors. Then we fit these data for interaction effect by examining how an increase in its influence might enhance or diminish the sales of medical service.

In order to examine the research question of how the presence of service diversity might change the distribution of service sales, we first fit the size of serviced patients and volume of votes data to the following multiple log-linear relationship as:

$$\ln(SP_i) = \beta_0 + \beta_1 \ln(BS_i) + \beta_2 \ln(VV_i) + \beta_3 DD_i + \beta_4 \ln(RR_i) + \beta_5 \ln(CT_i) + \epsilon_i$$

(4)

where $\beta_0$ is the coefficient of the constant term and $\beta_i, i=1,..., 5$, are the coefficients of independent variables, $\ln(\cdot)$ are the logarithmic transformations of those variables. All variables are defined in Table 1. The error term $\epsilon_i$ obeys normal distribution with mean 0 and variance $\sigma^2$.

**Results**

**Descriptive Statistics**
Within the sample data, statistics of the empirical experimental data is demonstrated in Table 2. On volume of votes, its total amount is 704,467, mean value 71 and median 39.

Table 2. Statistics of the empirical experimental data

<table>
<thead>
<tr>
<th>Variables</th>
<th>Min</th>
<th>1st quarter</th>
<th>Median</th>
<th>Mean</th>
<th>3rd quarter</th>
<th>Max</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP</td>
<td>11</td>
<td>342</td>
<td>857</td>
<td>1930</td>
<td>2122</td>
<td>69055</td>
<td>3201.977</td>
</tr>
<tr>
<td>BS</td>
<td>1</td>
<td>6</td>
<td>9</td>
<td>8.821</td>
<td>12</td>
<td>49</td>
<td>3.701</td>
</tr>
<tr>
<td>VV</td>
<td>5</td>
<td>17</td>
<td>39</td>
<td>71</td>
<td>86</td>
<td>1723</td>
<td>99.604</td>
</tr>
<tr>
<td>DD</td>
<td>0</td>
<td>1.842</td>
<td>2.441</td>
<td>2.408</td>
<td>3.037</td>
<td>4.850</td>
<td>0.893</td>
</tr>
<tr>
<td>RR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>2.746</td>
<td>3</td>
<td>5</td>
<td>0.934</td>
</tr>
<tr>
<td>CT</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>4.021</td>
<td>5</td>
<td>5</td>
<td>0.869</td>
</tr>
<tr>
<td>Ln(SP)</td>
<td>2.398</td>
<td>5.835</td>
<td>6.753</td>
<td>6.759</td>
<td>7.660</td>
<td>11.143</td>
<td>1.293</td>
</tr>
<tr>
<td>Ln(BS)</td>
<td>0</td>
<td>1.792</td>
<td>2.197</td>
<td>2.066</td>
<td>2.485</td>
<td>3.892</td>
<td>0.517</td>
</tr>
<tr>
<td>Ln(VV)</td>
<td>1.609</td>
<td>2.833</td>
<td>3.664</td>
<td>3.671</td>
<td>4.454</td>
<td>7.452</td>
<td>1.092</td>
</tr>
<tr>
<td>Ln(RR)</td>
<td>0</td>
<td>0.693</td>
<td>1.099</td>
<td>0.974</td>
<td>1.099</td>
<td>1.6094</td>
<td>0.279</td>
</tr>
<tr>
<td>Ln(Ct)</td>
<td>0</td>
<td>1.099</td>
<td>1.386</td>
<td>1.364</td>
<td>1.609</td>
<td>1.609</td>
<td>0.245</td>
</tr>
</tbody>
</table>

Note: Ln(·) are the logarithmic transformations of the variables. The degree of voted diversity (DD₂) is not transferred as Ln(·), because it is defined with entropy (logarithmic transformation included).

Moreover, the correlation among those variables were also examined on the whole data samples, as shown in Figure 3. The results illustrated the correlation between SP and degree of voted diversity (DD) is low (0.23), because the correlation between BS and DD is high (0.76). The correlation between logarithm of Size of serviced patients (SP) and that of volume of votes (VV) is 0.73 with confidence interval (0.72, 0.74), which suggests SP is high positively related with VV. These correlation probably suggested that much of variation of the response variable (SP) may be explained by the predictors.

Figure 3. Correlation among the variables within the experimental samples. The cells below the principal diagonal display the correlation among the variables in digital figures with 95% confidence intervals enclosed with parentheses. The upper triangle of cells illustrate the same information using pies in blue. The darker and more saturated the color, the greater the magnitude of the correlation. RR: Review rating; VV: logarithm of Volume of votes; SP: logarithm of Size of serviced patients; BS: logarithm of Breadth of voted specialties; CT: Clinic title; DD: Degree of voted diversity.

Lorenz curve
Lorenz curve\textsuperscript{[38]} was implemented to illustrate the cumulative distribution of the variables in graphical representation, as shown as Figure 4. Within the filtered original sample data, the curve shows for the bottom fraction (p) of doctor population, what fraction (L(p)) of serviced patients (SP), breadth of voted specialties (BS), volume of votes (VV), degree of voted diversity (DD), review rating (RR) and clinic title (CT) they have.

We found that the patterns of serviced patients, voted specialties, volume of votes, review rating (RR) and clinic title were all of inequality in the distribution of its doctor population. We also quantified the inequality using the Gini coefficient which was derived from the Lorenz curve. The results show that the Gini coefficient of serviced patients is very high, 0.626, followed by the volume of votes (0.562). The Gini coefficients of breadth of voted specialties and the degree of voted diversity are much moderate, 0.227 and 0.210 respectively. Meanwhile, the results of the controls variables, review rating and clinic title, are also of inequality in their distributions, with Gini coefficients 0.127 and 0.116 respectively. In total, the distribution of voted diversity generated by patient crowd voting process is more even than the intrinsic distribution of volume of votes and breadth of voted specialties, even to the distribution of serviced patients. An increase in the influence of the voted diversity on doctor’s specialties will reduce its Gini coefficient. This phenomenon indicated this common pattern of votes concentration and presented opportunities for various doctors to provide medical services in the niche specialty category. These niche specialty also encourage the diversification of medical services. However, information technology in online health community in particular had the potential to substantially increase the collective share of niche service, thereby creating a longer tail in the distribution of doctors’ specialties.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{lorenz_curve.png}
\caption{Lorenz Curve of the variables. Left subfigure illustrates the Lorenz curve of serviced patients (SP) and the predictors of patient crowdvotes aggregated service diversity, right subfigure illustrates the Lorenz curve of serviced patients (SP) and the control variables. BS: breadth of voted specialties, VV: volume of votes, DD: degree of voted diversity; RR: review rating, CT: clinic title. The x-axis refers to the bottom fraction (p) of doctor population, and the y-axis refers to the fraction L(p) of the variables of interest.}
\end{figure}

\textbf{Main Effect of Services Diversity}

The test for main effect was performed with regression estimation model (4) with the experimental data. We verified whether the main effects of service diversity on size of served patients for doctors in this specialty area. The values of standardized regression coefficients, standard errors, t-values, and p-values were reported for all variables, as well as the R-Squared values of the models, shown as Table 4.
For the whole samples, the coefficient of determination was very high ($R^2=98.1\%$), illustrating that the model had a good capacity to explain a substantial amount of variance in the dependent variable. The result demonstrates the significant and positive effect of the breadth of voted specialties ($\beta_1 =0.309$), volume of votes ($\beta_2 =0.745$) and degree of voted diversity ($\beta_3=0.073$) on size of serviced patients (SP). For the control variables, we can see that review rating ($\beta_4=0.810$) and clinic title ($\beta_5 =1.735$) also had positive associations with size of serviced patients. All of the estimates are statistically significant at a 0.1% level with $N=9,841$.

Furthermore, quartile Analysis was implemented to test the robustness of those results with the top 25% of the samples in the variables of volume of votes. The result also demonstrates the significant and positive effect of the breadth of voted specialties ($\beta_1 =0.246$), volume of votes ($\beta_2 =0.961$) and degree of voted diversity ($\beta_3=0.037$) on size of serviced patients (SP). All of the estimates are statistically significant at a 5% level with $N=2,461$ and $R^2= 0.991$. We also test the robustness of those models for all the samples with the binary transformations of the variables. All of the estimates are also statistically significant at a 0.1% level with $N=9,841$ and $R^2= 0.413$. To sum up, these empirical evidence further confirmed the impact of patient crowdvotes aggregated service diversity on doctors’ service sales in online health community.

Table 4. Results for the robustness of the main effects, quartile analysis and interaction effect of service diversity on size of served patients for doctors.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>t value</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.520</td>
<td>0.413</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Ln(BS)</td>
<td>0.309</td>
<td>0.038</td>
<td>8.062</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Ln(VV)</td>
<td>0.745</td>
<td>0.014</td>
<td>53.403</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>DD</td>
<td>0.073</td>
<td>0.018</td>
<td>3.928</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Ln(RR)</td>
<td>0.810</td>
<td>0.041</td>
<td>19.906</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Ln(CT)</td>
<td>1.735</td>
<td>0.027</td>
<td>64.121</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

| Intercept   | 0.014    | 0.755          | <0.001  |         |
| Ln(BS)      | 0.246    | 0.055          | 4.517   | <0.001  |
| Ln(VV)      | 0.961    | 0.031          | 30.678  | <0.001  |
| DD          | 0.037    | 0.019          | 1.912   | 0.056   |
| Ln(RR)      | 0.948    | 0.099          | 9.606   | <0.001  |
| Ln(CT)      | 0.903    | 0.061          | 14.688  | <0.001  |

| Intercept   | 0.052    | 0.413          | <0.001  |         |
| Bin(BS)     | 0.127    | 0.012          | 10.47   | <0.001  |
| Bin(VV)     | 0.521    | 0.009          | 55.21   | <0.001  |
| Bin(DD)     | 0.010    | 0.010          | 10.31   | <0.001  |
| Bin(RR)     | 0.228    | 0.015          | 15.56   | <0.001  |
| Bin(CT)     | 0.169    | 0.008          | 20.16   | <0.001  |

SP: Size of serviced patients, BS: breadth of voted specialties, VV: volume of votes, DD: degree of voted diversity, RR: review rating and CT: clinic title.

**Interaction Effects of Served Diversity**

As Table 4 demonstrated, all of the estimates are also statistically significant at a 0.1% with binary transformations of the variables. To gain a deeper understanding of the interaction between doctors’ service sales and the control variables, we examined the slopes of the patient
crowdvotes aggregated service diversity (including breadth of voted specialties, volume of votes, and degree of voted diversity) × control variables (clinic title, review rating) Interaction, shown as Figure 5. We adapted the spotlight analysis method as Fitzsimmons (2013) did, with which the analysis involves shifting the mean level of the outcome variable (Bin(SP)) and then conducting significance tests for an individual slope. We conducted this spotlight analysis at the binary transformation of breadth of voted specialties (BS) and volume of votes (VV), and degree of voted diversity (DD) in all cases, respectively.

As Figure 5 shows, the slope plots support our theoretical arguments: the treads of the doctors’ service sales kept increasing as the patient crowdvotes aggregated service diversity increased, especially with low review ratings. The larger the breadth of voted specialties was, the higher the mean level of doctor’s serviced patients was. Similar results were derived for volume of votes and degree of voted diversity. Comparing with figures 5(A) and 5(C), the results in figure 5(E) shows that the treads keep increasing as the clinical title grow larger, while the gap caused by degree of voted diversity becomes less. Comparing with figures 5(B) and 5(F), the results in figure 5(D) shows that the treads also keep increasing as the review rating grow larger, while the gap caused by degree of voted diversity become less. This result suggested that the patient crowdvotes aggregated service diversity has a larger positive impact on the doctors’ service sales when the review rating is low. In total, the spotlight analysis supported the proposed existence of influence and contagious effects of the patient crowdvotes aggregated service diversity on the doctors’ service sales.

![Figure 5](https://via.placeholder.com/150)

**Figure 5.** Slopes of patient crowdvotes aggregated service diversity × control variables Interaction. Sub figures (A), (C) and (E) deploy the binary transformations of BS, VV and DD × binary transformations of review rating (RR) interaction, respectively; Sub figures (B), (D)
and (F) deploy the binary transformations of BS, VV and DD × binary transformation of clinic title (CT) interaction, respectively.

Discussion
Principal Results

Within the retrospective study data, 9,841 doctors gained 704,467 votes of clinical specialties on the study online health community during Aug. 26, 2015-Aug. 25, 2017. One interesting finding based on Lorenz curves is that the patterns of both the labels of patient crowdsvotes aggregated service diversity (including encountered disease labels and online votes) and doctors’ service sales were of inequality in the distribution of its size of serviced patients in a OHC. The results also showed that the Gini coefficient of serviced patients was very high, 0.626, followed by the volume of votes (0.562). The distribution of voted diversity generated by patient crowd voting process is more even than the intrinsic distribution of volume of breadth and votes of voted specialties, even to the distribution of serviced patients. The correlation between logarithm of Size of serviced patients (SP) and those of volume of votes (VV) and breadth of voted specialties (BS) are 0.73 and 0.49, which suggests SP is high positively related with VV and BS. The correlation between SP and degree of voted diversity (DD) is relatively high (0.23), because the correlation between BS and DD is high (0.76). With the main effects analyses, the results suggested that all the variables abstracted from the patient crowds votes had positive impacts on doctors’ service sales in online health community. The patients crowdsvotes system on OHC provided channels for the patients to label the doctors’ specialties, which also reflected the primary and secondary diseases of their own encountered. The result provided empirical evidence that not only the patient crowdsvotes may increase the doctors’ service sales, but also the patients crowdsvotes contains the information of both the primary specialty of the doctors and the doctors’ service diversity.

To improve doctors’ service sales in the OHC, we recommended that managers in OHC perform should provide/recommend well-defined labels with high quality for users to vote with the feedback of patient crowdsvotes aggregated service diversity. The results of spotlight analysis suggested the larger the breadth of voted specialties was, the higher the mean level of doctor’s serviced patients was. We also found that at the same clinical title, increases in the influence of the crowdsvotes aggregated service diversity were consistently associated with an even or flatter distribution of doctors’ service sales. At the same level of review rating, the increases on patient crowdsvotes aggregated service diversity had positive impacts on doctors’ service sales. Moreover, the higher breadth of voted specialties and degree of voted diversity displayed a greater service sales with a higher review rating. This is consistent with the conjecture that large size of patient crowdsvotes aggregated service diversity with high review rating will have a more pronounced service distributed tail or less inequality of Doctors’ service sales. To sum up, our findings can help people to understand the current status of patients’ online labels can help us understand the service diversity for patients, but it should be noted that to criticize any doctor for providing fewer service diversity to the OHC would be very inappropriate. As the posters of Good Doctor Online platform says “Based on patients' self-introduction of their conditions, those comments presented by doctors can only be regarded as references rather than direct guidelines for diagnosis and treatment”, those doctors and patients should pay more attention to the rear labelled and voted disease cases through the online medical consultation service.

Limitations
Our empirical results cannot be used to explain all of the doctors’ specialties to serve patients, but only their OHC patient crowd voting process. Limitations in this study lie in the following aspects. First, all the data of patient crowd voting process (including size of specialty labels, number of votes and service diversity) and Doctors’ service sales were collected from one single OHC, the Good Doctor website. Since the size of each individual doctor’s specialty was calculated in the patient crowd voting process over two days (as the duration of data collection was from August 26, 2017 to August 27, 2017), a bias exists in the measure of time interval. Second, our study should be regarded as a starting point for further investigation, rather than a final causal statement about the patterns and influence of service diversity on the distribution of doctors’ service sales. Third, as the votes of labeled service were recorded for 2 years and changed as time passes, the status of the service diversity for each doctor also dynamically changed. The redundancy of the voted labels and measures could not be avoid in this study. We analyzed the main and interaction effects of patient crowdvotes aggregated service diversity on doctors’ service sales. In future work, a longitudinal observational study can be designed to investigate the dynamic mechanism. Fourth, the thresholds were preset in the data filter process, and more control variables (including hospital level, cities locations and doctors’ membership time of OHC, group diversity of doctors, etc.) could also be taken account into the model. As the samples did not completely conform to the standard normal distributions but were nevertheless supported [40], the samples may be transformed by logarithmic transformations and binary transformations according to the commonsense of the coauthors.

Conclusions
To investigate the impact of patient crowdvotes aggregated service diversity on doctors’ service sales in OHC, we designed and conducted a retrospective study with all data collected from the Good Doctor website. The OHC enabled patient crowds’ engagement and shared experience by creating labels of their encountered disease and voting online for the doctors. A multiple log-linear relationship was employed to fit the size of serviced patients and the service diversity, which was quantified from three aspects of the patient crowd voting, including breadth of voted specialties, volume of votes and degree of voted diversity. Our study provided empirical evidence that the patterns of both the labels of patient crowdvotes aggregated service diversity and doctors’ service sales were of inequality (as illustrated in Lorenz curves) in the distribution of its size of serviced patients in a OHC. Patient crowds’ online labels also led to differences in the doctors’ service sales online. The results suggested that the doctors’ service sales increased as the patient crowdvotes aggregated service diversity increased, and the treads kept increasing as the review rating increases, especially with low review ratings. Finally, our findings suggested that the higher breadth of voted specialties and degree of voted diversity displayed a greater service sales with a higher review rating, deploying less inequality of Doctors’ service sales. In the future, we could further investigate the factors affecting doctor service sales and their inequality by designing more observational studies. Then more insights on the casual effects of service patterns in OHC could be found through investigation of increment/decrement dynamic of doctors in the online medical consultation process.

Acknowledgements
This article is funded by the National Natural Science Foundation of China (No.71601026, No.71571105), China Postdoctoral Science Foundation (No.2016M602676) and international exchange program, Chongqing Science and Technology Commission (cstc2017zdcy-zdzx0046, cstc2017jcyjA0802).
Conflicts of Interest
None declared.

Abbreviations
BS  breadth of voted specialties
CT  clinic title
DD  degree of voted diversity
OHC Online health community
RR  review rating
SD  standard deviation
SE  standard error
SP  serviced patients
VV  volume of votes

References
32. Bohannon J. Having trouble hailing that taxi? This could be why. science. 2016.


