A Multi-Dimensional Context-Aware Healthcare Service Recommendation Method

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ABSTRACT

Due to the outbreak of COVID-19, online diagnosis and treatment services have developed rapidly, but it is not easy for patients to choose the appropriate healthcare service in the face of massive amounts of information. This article proposes a multi-dimensional context-aware healthcare service recommendation method, which consists of a healthcare service matching model and a healthcare service ranking model. The former first collects objective knowledge related to doctors and diseases to build a knowledge graph, then matches a group of healthcare services for patients according to the patient’s input; the latter selects five indicators from the doctor’s academic level, geographical location, public influence, reputation, etc. to build a TOPSIS model based on the entropy weight method to recommend the most appropriate healthcare services for patients. Finally, taking the patient in Shiyan as an example, the whole process of the method is demonstrated, and the feasibility of the method is verified.

KEYWORDS

BiLSTM, Topsis, Context-Aware Service Recommendation, Knowledge Graph, Online Healthcare Service, Sentiment Analysis, Web Service

INTRODUCTION

During the COVID-19 pandemic, online healthcare treatment has been widely used (Yang et al., 2020). Most online consultation platforms are passive service models, requiring patients to choose appropriate departments and doctors according to their conditions. However, it is not easy for most people to go to the appropriate department according to their symptoms. On the one hand, due to the diversity and complexity of medical knowledge, it is difficult for people to make correct decisions due to a large amount of information on the Internet. On the other hand, some people may follow...
experts blindly, and they may not book the most suitable experts, resulting in a shortage of medical resources. In response to these problems, H. Jiang and Xu (2014) proposed a doctor-recommended method, but this method requires patients to understand their disease, but it is difficult for most patients to describe their diseases accurately. Ju and Zhang (2021) proposed an online pre-diagnosis doctor recommendation model that fused ontology features and disease text mining, but other attributes of doctors and other behavioral information of patients were not considered in this model. To sum up the research, the following problems still exist:

1. Most of the existing studies aim to recommend offline doctors, ignoring the vast potential of online healthcare services.
2. At present, most of the recommendations are based on the objective information of the doctor, ignoring the context of the healthcare services and patients.

In terms of the current form in which the COVID-19 pandemic will coexist with human beings for a long time, online healthcare treatment will continue to flourish, and there will be more and more online healthcare services. As of July 2021, the Haodaifu online platform (https://www.haodf.com/) has collected the information of more than 790,000 doctors from nearly 10,000 regular hospitals across the country and more than 240,000 doctors have registered on the platform. Dingxiang Doctor (https://dxy.com/) has more than 50,000 professional doctor teams from Class A tertiary and higher-level hospitals. With the help of Dingxiangyuan (https://portal.dxy.cn/), Dingxiang Doctor covers more than 70% of the professional doctor resources in the country. It can be seen that users have requirements, and there are many online healthcare services, but the resources among the platforms are fragmented, and there is no resource exchange. Therefore, it is significant to establish a connection between patients and Internet resources and recommend the most appropriate healthcare service.

This article proposes a multi-dimensional context-aware healthcare service recommendation method, which will recommend the most appropriate healthcare service based on the symptoms described by patients and context factors. Specifically, the contributions of this article are as follows:

1. A multi-dimensional context-aware healthcare service recommendation method is proposed, which will recommend the most appropriate healthcare service for the patient according to the symptoms input by the patient and combining multiple dimensions.
2. A sentiment analysis method for patient reviews is proposed, which uses bidirectional Long Short-Term Memory (BiLSTM).
3. Select multiple indicators from subjective and objective perspectives to construct evaluation models to evaluate doctors and help patients make the most appropriate healthcare service decisions.

The rest of this article is structured as follows: the Background section summarizes the related work of the study. The Proposed Method section first presents the overall architecture of the method, and then introduces the healthcare service-matching model and healthcare service-ranking model, respectively. The Case Study section presents the entire method process with patient case and verifies the feasibility of the method. The Conclusion and Future Work section summarizes the full text and proposes future work.

**BACKGROUND**

The general process of web service recommendation is first to collect the user’s basic information, historical call records, user preferences, and other data, establish the user’s usage model, and make
recommendations based on the user’s usage model (Zhang et al., 2013). The key to web service recommendation is how to use data mining and machine learning techniques to predict user needs.

The context-aware recommender system (CARS) has been widely used to achieve recommendations that are more accurate. Dey (2001) defines context as any information that can be used to characterize the situation of an entity. According to Dey’s definition, context can be any information that describes the current situation of an entity. Chen et al. (2013) proposed a novel location-aware web service recommendation approach. Quality of service (QoS) records observed by users was first collected, and then users with similar QoS observations were grouped to generate recommendations. Location information also needed to be considered when clustering users and services. S. Li et al. (2017) proposed a web service recommendation system that considered feature similarity of different service contexts. The system first extracted context attributes from web service description language (WSDL) files, then clustered them according to the feature similarity of web services, and finally, the improved matrix decomposition method was used to recommend services to users. Mezni et al. (2020) proposed a context-aware web service recommendation approach focusing on the time dimension. First, the particle swarm optimization and K-means were mixed by excluding users who shared a few standard web services with active users in a specific context, and then the Slope One method was used to predict the missing rating in the user’s current context. Finally, a recommendation algorithm was proposed to return the highest-rated service. Fan et al. (2017) proposed a context-aware services recommendation method based on temporal-spatial effectiveness. In this method, first, the effectiveness of spatial correlations between the user’s location and the service’s location on user preference expansion was modeled. Next, they proposed an enhanced temporal decay model considering the weighted rating effect in the similarity computation to improve prediction accuracy.

However, the above studies are not aimed at a specific domain. L. Wang et al. (2020) proposed an internet medical service recommendation method based on collaborative filtering. The method first used the analytic hierarchy process (AHP) to achieve initial weight allocation. Then, based on the evaluation methods of doctors and hospitals, the article established the user interest model, and K-means clustering was carried out for users. Finally, combined with the collaborative filtering recommendation method, the dynamic recommendation was made to users. This method needs to calculate the similarity between patients through the patients’ behavior logs and then realize the recommendation. However, there are often many new users for the healthcare platform, the behavior log is not easy to obtain, and there are often many differences between patients, such as geographic location. Dhas and Jeyanthi (2017) used QoS values to recommend the best services for healthcare, health professionals, and diagnostic centers. The method tracked users’ location and then recommended users based on the QoS value. However, this method relied on QoS values given by the user and did not take into account some of the individual attributes of healthcare, health professionals, and diagnostic centers. Meng and Xiong (2021) proposed a doctor recommendation based on graph computing and the Latent Dirichlet Allocation (LDA) topic model, but this method did not consider patient reviews.

For healthcare service recommendations, people pay more attention to the fitness of healthcare services with the patient’s situation and symptoms. In this case, the context of patient and healthcare services needs to be fully considered. This article proposed a multi-dimensional context-aware healthcare service recommendation method. The method consists of two models. The first is a healthcare service-matching model, which builds a healthcare service knowledge graph, and matches a group of healthcare services according to the symptom description input by the patient. The second is the healthcare service-ranking model, which selects the evaluation indicators of healthcare services from multiple perspectives, and builds an improved technique for order of preference by similarity to ideal solution (TOPSIS) model based on the entropy weight method.
PROPOSED METHOD

Overall Architecture

In this study, doctors are the central part of healthcare services, and there is very little behavioral information that can be used between newly registered users and new healthcare services. Therefore, it is challenging to recommend users’ neighbors by using the collaborative filtering algorithm. This study will make the following assumptions:

1. Online healthcare services will continue to flourish.
2. Current online healthcare resources can be packaged into web services; these services have a unified registry to be interconnected.

The multi-dimensional context-aware healthcare service recommendation method proposed in this article is divided into three steps. The first step is data processing, which is to segment the natural language input by patients and remove pause words. The second step is to use the healthcare service-matching model. In this model, a set of healthcare services good at treating the disease is matched according to the patient’s description. The third step is to use the healthcare service-ranking model. In this model, the matched healthcare services are ranked according to the determined indicators and scoring model, and the most suitable healthcare service is returned to the patients. Firstly, according to the information of patients and doctors, this article crawls the data of various indicators, calculates the value of each indicator, and finally brings these indicators into the improved TOPSIS algorithm based on the entropy weight method to obtain the ranking of healthcare services. Figure 1 shows the flow of the entire method.

Healthcare Service-Matching Model

The schema of the knowledge graph in this study will refer to the Unified Medical Language System (UMLS). UMLS brings together many widely used vocabularies and standards in biomedicine (Jing, 2021) and has the characteristics of integration, cross-domain, and instrumentalization. UMLS

Figure 1. Architecture diagram of multi-dimensional context-aware healthcare service recommendation method
integrates more than two million names for some 900,000 concepts from more than 60 biomedical word families and 12 million relationships between these concepts (Bodenreider, 2004). Considering that this work only involves healthcare service recommendations, this article summarizes ontologies such as “disease,” “symptom,” “population,” “body structure,” “department,” “hospital,” and “doctor” from UMLS. The relationship between ontologies in this article will refer to Yu and Xiao (2021), and the schema is shown in Figure 2.

This article extracts knowledge on platforms such as Haidaofu, Dingxiang Doctor, and WeDoctor (https://www.guahao.com/), which provide relevant information about doctors. Information such as the affiliation of doctors and diseases that doctors are good at can be obtained from these platforms to build a knowledge graph, and Neo4j (Z. Jiang et al., 2021) is used to store the knowledge graph. In this article, doctors are matched for patients according to the similarity between the patient and the doctor. The viable system model (VSM) model (Di Noia et al, 2021) is used to calculate the similarity.

**Healthcare Service-Ranking Model**

*Indicator Selection*

For a group of healthcare services obtained by the healthcare service-matching model, this article will select multiple indicators from the subjective and objective basis to evaluate the alternative healthcare services.

1. **Academic Levels:** The quantity and quality of a doctor’s papers can often reflect a doctor’s academic level. This article selects the representative Web of Science database (E. Liu, 2002) as the data source, an internationally recognized database reflecting the level of scientific research. Therefore, the number of papers retrieved from this database is taken as the number of papers by doctors. Moreover, the quality of a doctor’s papers is assessed using the average impact factors of the journals in which the papers were retrieved. The number of papers and the quality of papers

![Figure 2. The schema of the knowledge graph](image-url)
are both positive indicators. The higher the number of papers, the higher the impact factor, which means the higher the academic level of a doctor.

2. **Geographical Location:** Online healthcare services often can only provide patients with a preliminary diagnosis. Specific examinations and further treatment still need to be carried out in offline hospitals. This article also considers the distance between the patient’s location and the doctor’s hospital when recommending online healthcare services. In practice, there are often cases where the Euclidean distance from a specific place to two other cities is not much different, but the actual distance is quite different. Therefore, the actual distance is used when expressing the distance from the patient to the target hospital. Considering that the influence factor of distance in online diagnosis and treatment is not very large, this article will square the actual distance.

When considering the distance from the patient to the hospital, this article will also consider the medical level of the target location. Cities with higher medical levels can often provide better medical services to patients. Therefore, the number of Class A tertiary hospitals in each city measures the local medical level.

By combining the above two indicators, this article defines the ratio of the number of Class A tertiary hospitals to the square root of the actual distance as the geographic factor $\alpha$, and its calculation method is described in formula 1:

$$\alpha = \frac{n}{\sqrt{s}}$$

where $n$ is the number of Class A tertiary hospitals in each city, and $s$ is the distance between the patient and the target hospital. For the geographical factor, the actual distance is a negative indicator. The smaller the actual distance, the better, while the medical level is a positive indicator. The higher the medical level, the better. Hence, the geographical factor is a positive indicator.

3. **Public Influence:** This study aims to analyze the correlation between the returned results and the doctor. The results returned by a direct search on Baidu (https://www.baidu.com/) are not necessarily related to the doctor. To a certain extent, the exposure of a doctor can reflect the popularity of the doctor. This article searches on Baidu using the doctor’s name and workplace as keywords, crawls the title and abstract of each returned result, performs word segmentation on the obtained information, and removes stop words. Finally, keyword matching is performed between the text and the relevant information of the doctor to determine whether the returned result is related to the doctor. For each doctor, this article collects the top 50 reports on the Baidu search engine, counts the number of valid positive reports, and uses this number to measure the doctor’s public influence. The number of valuable reports is a positive indicator. The greater the number of valuable reports, the greater the public influence of a doctor.

4. **Reputation:** Due to the information asymmetry between doctors and patients, the reviews of other patients are often an essential reference. Although many platforms provide scoring and review services for patients, the following two phenomena are found by analyzing the reviews and scoring of doctors from different patients:
   a. Different online healthcare platforms have different scoring standards. For example, the scoring system on the Dingxiang Doctor platform is 5 points, while the scoring system on the WeDoctor platform is 10 points.
   b. There is a problem of mismatch between scores and reviews. For example, Figure 3 shows three patient reviews collected from the Dingxiang Doctor platform. It can be seen that the reviews made by the patient are negative, but the scores are still the highest.
Therefore, if the patient’s score directly evaluates the doctor’s reputation, there will be problems because the scoring mechanisms of different platforms are different, and the score does not match the actual review. In cases where the use of patient scores to measure physician reputation is not entirely reliable, this article conducts a sentiment analysis of patient reviews. Text sentiment analysis analyzes subjective texts with vibrant colors to mine their emotional tendencies and classify emotional attitudes (T. Wang & Yang, 2021). To accurately analyze the emotional tendency of each patient’s evaluation, this article will use the bidirectional long short-term memory networks (BiLSTM) model (G. Liu & Guo, 2019) to analyze the sentiment of the patient’s reviews.

Recurrent neural network (RNN) (Huddar et al., 2021) is a neural network with short-term memory ability, which has been widely used in natural language processing. However, RNN has the problem of gradient explosion and gradient disappearance when processing long text. Long short-term memory (LSTM) (Ma et al., 2018) is an improvement to RNN that was initially developed to address the long-term dependence of RNN. Unlike RNN, the neural unit of LSTM contains threshold function constraints such as forget, input, and output gates, thereby conditionally deleting the neuron state and adding information according to the degree of importance. The general formula for the gate structure is described in formula 2:

\[ g(x) = \sigma(Wx + b) \]  

(2)

where \( \sigma \) is the sigmoid activation function, \( W \) is the weight matrix of the gate, and \( b \) is the offset vector.

The unique structure of LSTM solves the problem that the data of long texts, which is input at an earlier time, cannot be remembered, and to some extent, it can avoid the problems of gradient disappearance and gradient explosion (Z. X. Liang et al., 2021). LSTM is unidirectional and cannot obtain the previous information in reverse. The BiLSTM contains two LSTM networks, one layer is used to transmit information forward, and the original dataset set is used as input. The other layer is used for transmitting information in reverse, taking the reversed dataset as input. Such a structure can effectively extract past and future contextual information simultaneously.
The specific steps of using BiLSTM to perform sentiment analysis on the collected patient reviews are as follows: First, perform word segmentation on the patient reviews collected from the online healthcare platform. Then this article uses Word2Vec to represent words with word vectors and puts the obtained word embeddings into BiLSTM for training. The final result will be output in $[0, 1]$. When the output is higher than 0.5, the review is considered a positive review, and when the output is less than 0.5, the review is considered a negative review.

In this article, 4,000 patient reviews were collected from the Dingxiang Doctor online healthcare platform. The labels of positive reviews were set to one and the labels of negative reviews were set to zero through manual labeling. Then, 10% of them were extracted as the cross-validation set, a graph of the accuracy and loss of the sample set was then made with the iteration cycle, as shown in Figure 5. In Figure 5, early stopping was set in advance, and it is found that the loss of five consecutive cycles after the twelfth iteration cycle no longer decreased, so it exited in the sixteenth cycle. The final accuracy rate in the validation set finally reached 97.56%.

After crawling the reviews of each doctor and performing sentiment analysis, this article defines the favorable rate $\beta$ to measure the doctor’s reputation. The calculation method is as follows in formula 3:

$$\beta = \frac{d}{N}$$

where $d$ is the number of positive reviews by patients of doctors, and $N$ is the total number of reviews. This indicator is a positive indicator. The higher the doctor’s favorable rate, the better the doctor’s reputation.

**Improved TOPSIS Algorithm Based on Entropy Weight Method**

TOPSIS (Sun et al., 2016) is a sorting method approximating the ideal solution. The principle calculates the distance between the alternatives and the positive ideal solution, and the negative ideal solution.
to sort. The positive ideal solution is the virtual best solution, and the negative ideal solution is the virtual worst solution. The Euclidean distance is used when calculating the distance. When a scheme is closest to the positive ideal solution and far away from the negative ideal solution, the scheme is optimal among the alternatives. However, in the traditional TOPSIS algorithm, the weights of the indicators are obtained by the expert opinion survey method or the analytic hierarchy process, which are highly subjective (Y. Y. Li et al., 2008). This article uses the entropy weight method to assign weights to the indicators. Entropy describes the degree of chaos in the system. The indicator weight is determined by the influence of the relative change degree of the indicators on the system.

The steps of the improved TOPSIS method based on the entropy weight method are as follows:

**Step 1:** Assuming there are \( n \) services and \( m \) indicators, construct the original data as in formula 4:

\[
X = \begin{bmatrix}
    x_{11} & x_{12} & \cdots & x_{1m} \\
    x_{21} & x_{22} & \cdots & x_{2m} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{n1} & x_{n2} & \cdots & x_{nm}
\end{bmatrix}
\]  

(4)

where \( x_{nm} \) is the \( m \)-th indicator value of the \( n \)-th service. For example, \( x_{11} \) is the first indicator value of the first healthcare service. There are five indicators in the model constructed in this article, so the value of \( m \) is five.

**Step 2:** Normalize the original matrix. The indicators in this paper are all economic indicators to be directly normalized. The normalized formula is shown in formula 5:

\[
z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} (x_{ij})^2}}
\]  

(5)

where \( z_{ij} \) is the normalized data and \( x_{ij} \) is the data in the original matrix. The resulting normalized matrix is shown in formula 6:

\[
Z = \begin{bmatrix}
    z_{11} & z_{12} & \cdots & z_{1m} \\
    z_{21} & z_{22} & \cdots & z_{2m} \\
    \vdots & \vdots & \ddots & \vdots \\
    z_{n1} & z_{n2} & \cdots & z_{nm}
\end{bmatrix}
\]  

(6)

**Step 3:** Calculate the weight using the entropy weight method. First, calculate the probability matrix \( P \), the calculation formula of each element \( p_{ij} \) in \( P \) is as in formula 7:

\[
p_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}}
\]  

(7)
where $z_{ij}$ is the standardized data. For the $j$-th index, the calculation method of its information entropy is shown in formula 8:

$$
e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln(p_{ij})(j = 1, 2, \cdots, m)$$

(8)

where $n$ is the total number of alternatives, $m$ is the total number of indicators, $e_j$ is the information entropy of the $j$-th indicator, and the larger the value is, the less information the $j$-th index has. Then calculate the utility value of the information. The calculation method is as in formula 9:

$$d_j = 1 - e_j$$

(9)

where $d_j$ is the information utility value of the $j$-th indicator, and $e_j$ is the information entropy of the $j$-th indicator. The greater the information utility value, the more information the indicator reflects. The entropy weight of each indicator can be obtained by normalizing the information utility value, and the calculation method is as shown in formula 10:

$$w_j = d_j / \sum_{j=1}^{m} d_j(j = 1, 2, \cdots, m)$$

(10)

where $w_j$ is the weight of the $j$-th indicator, and $d_j$ is the information utility value of the $j$-th indicator.

**Step 4:** Calculate the weighted data matrix according to formula 11:

$$y_{ij} = w_j z_{ij}$$

(11)

The weighted data matrix is shown in formula 12:

$$Y = \begin{bmatrix}
y_{11} & y_{12} & \cdots & y_{1m} \\
y_{21} & y_{22} & \cdots & y_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
y_{n1} & y_{n2} & \cdots & y_{nm}
\end{bmatrix}$$

(12)

The positive ideal solution and the negative ideal solution are calculated according to the weighted data matrix, and the calculation method is as shown in formula 13:

$$Y^+ = \{y_{1}^+, \cdots, y_{m}^+\}, y_j^+ = \max_{1 \leq i \leq n}\{y_{ij}\}$$

$$Y^- = \{y_{1}^-, \cdots, y_{m}^-\}, y_j^- = \min_{1 \leq i \leq n}\{y_{ij}\}$$

(13)

where $Y^+$ is the positive ideal solution, and $Y^-$ is the negative ideal solution.
**Step 5:** Calculate the distance, and the distance from each scheme to the positive ideal solution is as shown in formula 14:

\[
D_i^+ = \sqrt{\sum_{j=1}^{m} (Y_j^+ - y_{ij})^2}
\]

where \(Y_j^+\) is the positive ideal solution of the \(j\)-th indicator, and \(y_{ij}\) is the \(j\)-th indicator value of the \(i\)-th scheme.

The distance from each scheme to the negative ideal solution is as shown in formula 15:

\[
D_i^- = \sqrt{\sum_{j=1}^{m} (Y_j^- - y_{ij})^2}
\]

where \(Y_j^-\) is the negative ideal solution of the \(j\)-th indicator, and \(y_{ij}\) is the \(j\)-th indicator value of the \(i\)-th scheme.

**Step 6:** Calculate the comprehensive evaluation index of each scheme and the calculation method is shown in formula 16:

\[
S_i = \frac{D_i^-}{D_i^+ + D_i^-}
\]

where \(D_i^+\) is the distance from the \(i\)-th scheme to the positive ideal solution, \(D_i^-\) is the distance from the \(i\)-th scheme to the negative ideal solution, and \(S_i\) is the comprehensive evaluation index of the \(i\)-th scheme.

**CASE STUDY**

This section will verify the feasibility of the method proposed in this article. A patient in Shiyan was used as an example to demonstrate the whole process of the method. The patient’s description of the condition was “nausea, vomiting, stomach ache, diarrhea.” According to the disease description input by the patient, the input natural language was segmented, the pause words were removed, and the processed text was passed through the healthcare service-matching model. The matching results are shown in Table 1.

Then, according to each indicator’s definition and calculation method, each indicator’s value was calculated. For the academic level, the doctor’s name and workplace were used as keywords to search in the Web of Science database, the number of papers was counted, the journals to which the papers belonged were recorded, and the average impact factor of the journals was calculated. The number of papers in the alternative scheme was 7, 13, 34, 10, and 7, and the average impact factors were 7.594, 2.289, 6.654, 3.615, and 4.631, respectively. For the geographic location, the location of each doctor’s hospital was obtained in the alternative scheme and the number of Class A tertiary hospitals in the city where each hospital is located was obtained. The geographic factors for each alternative were 1.411, 2.190, 1.700, 1.416, and 1.427. For public influence, each doctor was searched on Baidu, and the number of valid reports obtained after filtering was 21, 42, 48, 29, and 45, respectively. For the doctor’s reputation, the authors first went to each platform to crawl the patient reviews of the
corresponding doctor, and then put the crawled reviews into BiLTM for sentiment analysis. The favorable rate of each doctor was 0.94, 1, 0.99, 0.92, and 0.95. The results are summarized in Table 2.

According to the entropy weight method, the weights of each indicator were calculated as 0.6073, 0.2272, 0.0460, 0.1181, and 0.0014. The final comprehensive evaluation index of each healthcare service is shown in Table 3.

It can be seen from Table 3 that the healthcare service with the highest comprehensive index was Doctor Yao, which will eventually be recommended as the best healthcare service for patients. Specifically, Doctor Yao’s number of papers and number of valid reports ranked first among the five schemes, and the average impact factor, geographical factor, and favorable rate ranked second among the five schemes. Moreover, the recommended result was also in line with the patient’s expectations through the patient’s feedback. Therefore, it is also the most likely recommended solution objectively.

**CONCLUSION AND FUTURE WORK**

This article proposes a multi-dimensional context-aware healthcare service recommendation method consisting of a healthcare service-matching model and a healthcare service-ranking model. In the

<table>
<thead>
<tr>
<th>Doctor</th>
<th>City</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doctor Xiong</td>
<td>Wuhan</td>
</tr>
<tr>
<td>Doctor Li</td>
<td>Shiyan</td>
</tr>
<tr>
<td>Doctor Yao</td>
<td>Xi’an</td>
</tr>
<tr>
<td>Doctor Jiang</td>
<td>Wuhan</td>
</tr>
<tr>
<td>Doctor Xu</td>
<td>Wuhan</td>
</tr>
</tbody>
</table>

Table 2. The value of each scheme’s indicators

<table>
<thead>
<tr>
<th>Doctor</th>
<th>Number of Papers</th>
<th>Average Impact Factor</th>
<th>Geographic Factor</th>
<th>Number of Valid Reports</th>
<th>Favorable Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doctor Xiong</td>
<td>7</td>
<td>7.594</td>
<td>1.411</td>
<td>21</td>
<td>0.94</td>
</tr>
<tr>
<td>Doctor Li</td>
<td>13</td>
<td>2.289</td>
<td>2.190</td>
<td>42</td>
<td>1.00</td>
</tr>
<tr>
<td>Doctor Yao</td>
<td>34</td>
<td>6.654</td>
<td>1.700</td>
<td>48</td>
<td>0.99</td>
</tr>
<tr>
<td>Doctor Jiang</td>
<td>10</td>
<td>3.615</td>
<td>1.416</td>
<td>29</td>
<td>0.92</td>
</tr>
<tr>
<td>Doctor Xu</td>
<td>7</td>
<td>4.631</td>
<td>1.427</td>
<td>45</td>
<td>0.95</td>
</tr>
</tbody>
</table>

Table 3. Healthcare service-ranking model results

<table>
<thead>
<tr>
<th>Doctor</th>
<th>Comprehensive Evaluation Index</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doctor Xiong</td>
<td>0.1556</td>
<td>2</td>
</tr>
<tr>
<td>Doctor Li</td>
<td>0.1374</td>
<td>3</td>
</tr>
<tr>
<td>Doctor Yao</td>
<td>0.5174</td>
<td>1</td>
</tr>
<tr>
<td>Doctor Jiang</td>
<td>0.0806</td>
<td>5</td>
</tr>
<tr>
<td>Doctor Xu</td>
<td>0.1092</td>
<td>4</td>
</tr>
</tbody>
</table>
healthcare service-matching model, the relationship between entities is summed up, the schema of the knowledge graph is constructed, and the information of doctors, disease symptoms, and other information are collected on each platform. This knowledge is integrated into a knowledge graph and stored in the Neo4j graph database. Finally, according to the patient’s description, the VSM model calculates the similarity between the patient and the doctor, and a group of healthcare services is matched for the patient. For the academic level, this article selects the number of papers in the Web of Science database and the average impact factor to measure. For the geographical location, this article selects the actual distance from patients to the hospital and the number of Class A tertiary hospitals where the hospital is located. The actual distance can reflect how long it takes for patients to get to the target hospital, and the number of Class A tertiary hospitals can reflect the local medical level. The ratio of the number of Class A tertiary hospitals to the square root of the actual distance is defined as the geographic factor to measure geographic location. For the public influence of doctors, this article selects the number of valuable reports of doctors that can be searched using the Baidu search engine to measure. For doctor’s reputation, this article proposes a patient review analysis method based on BiLSTM, which inputs each doctor’s reviews for sentiment analysis and calculates the favorable rate to measure the doctor’s reputation. Then, an improved TOPSIS algorithm based on the entropy weight method is used to synthesize the above indicators to obtain the ranking of healthcare services. To verify the method’s feasibility, the whole process proposed in this article is demonstrated with a patient in Shiyan, and the most suitable healthcare service was successfully recommended for the patient.

In the future, the authors will collect more patient samples for experiments to demonstrate the effectiveness of this method. In addition, more indicators will be considered to provide patients with more accurate healthcare service recommendations.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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