J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 1927--1948

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

A Study on Trust Clustering of Perceived Recommendations Considering Patient's Trust Propensity in the Context of "Internet+Healthcare" Services

Jin Yin[1], Boyu Zhang[1,✉], Xiaoqian Huang[1]

[1] *College of Economics and Management, Xiamen University of Technology, Xiamen, Fujian, 361024, China*

ABSTRACT

"Internet + medical health" service is an important direction of current medical development. The high interactivity between doctors and patients in online medical services and the massive and dynamic nature of recommended information have brought new challenges to the platform's analysis of patient perceived trust. It is difficult for the trust transfer model to process massive information in real time. Clustering massive recommended trust is an effective solution, but data clustering is difficult to process simultaneously with the perceived recommendation trust tendency, which brings about the problem of perceived recommendation trust clustering. How to measure the trust tendency reflected in the clustering of patient perceived recommendation trust is a difficult problem faced by the trust transfer model in the context of Internet medical health services. This paper proposes a two-stage research idea of " conversion first, clustering later". Intuitive fuzzy sets are used to measure the fuzziness of patient perceived recommendation trust, and combined with sentiment dictionary, density clustering method and other methods to cross and penetrate each other, a patient perceived recommendation trust clustering method is constructed in the context of Internet medical health services. Finally, data experiments were conducted using the real data of the top 17 doctors on the Haodafu online platform to verify the effectiveness of the method. This method can reflect the subjectivity and ambiguity of patients' perceived trust, provide a solution for the processing of massive recommendation information, contribute to the research on the improvement of trust transfer method system, and provide method support for predicting and analyzing the trust measurement of patients in the context of Internet medical health services. The model proposed in this paper can be used as the core of the trust-based recommendation system in Internet medical care, and help Internet medical platforms formulate precise strategies for doctors.

Keywords: Internet medical care, trust transfer, intuitionistic fuzzy sets, clustering

✉ Corresponding author.

E-mail address: 2121021034@stu.xmut.edu.cn (B. Zhang).

Received 10 January 2024; Revised 25 May 2024; Accepted 20 October 2024; Published Online 16 April 2025.

DOI: 10.61091/jcmcc127b-108

© 2025 The Author(s). Published by Combinatorial Press. This is an open access article under the CC BY license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The rapid development of information technology and the continuous improvement of people's health awareness have facilitated the rapid development of the online medical information service industry [1]. Nowadays, online consultation has become an important means for patients to obtain health information and get social support for medical decision-making [2]. The China Internet Network Information Center (CNNIC) report shows that the scale of online medical users reached 298 million by December 2021, and more and more patients began to consult about diseases through online medical platforms [3-4]. Under the influence of the new coronary pneumonia epidemic, “can't go out, but need to see a doctor” is the need of many patients, and online consultation has changed the traditional medical model, breaking the boundaries of time and space, and providing a new channel for patients to carry out disease counseling, so that the patient and the doctor can interact and communicate at any time and any place [5-7]. As a new medical service model, the emergence of online medical platforms has improved the efficiency of patients' medical treatment, met the needs of many common people nowadays, and brought many health dividends to the society [8-9].

In recent years, online medical platforms have introduced a variety of health service modes, including telephone consultation, graphic consultation, and outpatient appointment, enabling doctors to provide multi-level, diversified, and more accurate services according to patients' individual needs [10-11]. Nowadays, this new online consultation mode in online medical platforms is widely accepted and gradually becomes an effective complementary way for patients to seek medical treatment, as well as an important channel for users to obtain health knowledge and medical decision support [12-13]. Typically, patients need to choose a suitable doctor for consultation from a large number of doctors providing online consultation services according to their own health needs, and they can also browse the consultation records of similar patients on the consultation platform to solve their health problems [14-15]. However, with the increase in the number of registered patients and doctors, the huge amount of information on online medical platforms and the uneven quality of related websites, patients lack professional medical knowledge and experience, making it difficult for them to identify useful information from the massive amount of information and find suitable doctors for consultation, thus reducing patient satisfaction [16-18]. Therefore, analyzing the influencing factors of patients' doctor selection behavior in online medical platforms, recommending suitable doctors for patients, and then improving patient satisfaction and reducing doctor-patient conflicts have become the concerns of many scholars [19-20].

Trust, as the core and foundation of doctor-patient relationship, largely determines users' willingness to use online consultation services [21-22]. At present, for the study of doctor-patient trust in the online environment, scholars at home and abroad mainly focus on the study of the relationship between the quality of online medical information and trust, and there are fewer studies on doctor-patient trust of online consultation services. Therefore, it is necessary to study the patients' perceived recommendation trust in online medical services [23-24].

Trust is a key issue in Internet medical research. Domestic and foreign scholars have conducted extensive research on patients' perceived trust and medical behavior decisions in the context of Internet medical services. Patients' perceived trust can be measured by the trust transfer model; patients receive a lot of information and then make decisions, which is a multi-attribute decision; patients' subjective perceived trust is extremely fuzzy, and the intuitionistic fuzzy set method can well characterize this uncertainty; at the same time, there is a high perceived risk, and when facing conflicting recommendation information, prospect theory can be used to balance and synthesize relevant information. Therefore, based on relevant research, this paper expands the framework of the traditional trust transfer model, combines intuitionistic fuzzy sets with multi-attribute decision-making, prospect theory and other methods, and constructs a patient-perceived recommendation trust transfer model in Internet medical care based on intuitionistic fuzzy sets.

2. Related research methods

This paper uses intuitionistic fuzzy sets to measure the perceived recommendation trust value of patients, and adopts a method based on sentiment dictionary to calculate the sentiment score of the review text, and then converts the objective review text into perceived recommendation trust intuitionistic fuzzy sets. Finally, the perceived recommendation trust is clustered based on the density clustering method. The specific content of this method is introduced below.

Perception recommendation trust intuitionistic fuzzy sets

The patient's perceived recommendation trust is characterized by uncertainty and fuzziness, which is the key difference between the trust transfer model with people as the main body and the traditional trust transfer model with computers as the main body. Intuitive fuzzy sets introduce the dimension of "hesitation" based on the "membership" and "non-membership" of fuzzy theory, which can effectively express the fuzziness of human perception and more accurately reflect the uncertainty characteristics of perceived trust. Suppose the patient's perceived recommendation trust intuitive fuzzy set is represented by $P=\langle \alpha,\beta,\pi \rangle$, where fuzzy membership $\alpha \in [0,1]$, fuzzy non-membership $\beta \in [0,1]$, hesitation $\pi = 1-\alpha-\beta$, and α,β,π meet the conditions $\alpha+\beta+\pi=1$. The basic rules of intuitionistic fuzzy set operations used in this paper are:

1) Positive multiplication operation of intuitionistic fuzzy sets:. When the intuitionistic fuzzy set P is multiplied by a positive number λ, the multiplication formula of the intuitionistic fuzzy set is:

$$\lambda P=\langle 1-(1-\alpha)^{\lambda},\beta^{\lambda},(1-\alpha)^{\lambda}+\beta^{\lambda}\rangle \tag{1}$$

2) Addition operation of intuitionistic fuzzy sets:. The addition formula of two $P_2=\langle \alpha_2,\beta_2,\pi_2\rangle$ intuitionistic fuzzy sets is: $P_1=\langle \alpha_1,\beta_1,\pi_1\rangle$

$$P_1+P_2=\langle \alpha_1+\alpha_2-\alpha_1\alpha_2,\beta_1\beta_2,\pi_1+\pi_2+\alpha_1\alpha_2-\beta_1\beta_2-1\rangle \tag{2}$$

3) Subtraction operation of intuitionistic fuzzy sets. Since there is no direct subtraction operation for intuitionistic fuzzy sets, the method in the reference paper is used here. The subtraction operation formula of the sum of two $P_2=\langle \alpha_2,\beta_2,\pi_2\rangle$ intuitionistic fuzzy sets is: $P_1=\langle \alpha_1,\beta_1,\pi_1\rangle$

$$P_1-P_2=\langle \alpha_1+\beta_2-\alpha_1\beta_2,\beta_1\alpha_2,1-\alpha_1-\beta_2+\alpha_1\beta_2-\beta_1\alpha_2\rangle \tag{3}$$

4) Negative multiplication operation of intuitionistic fuzzy sets. Also referring to the above paper, when the intuitionistic fuzzy set P is multiplied $-\lambda$, the multiplication formula of the intuitionistic fuzzy set is:

$$(-\lambda)P=\langle \beta^{\lambda},1-(1-\alpha)^{\lambda},(1-\alpha)^{\lambda}+\beta^{\lambda}\rangle \tag{4}$$

5) Intuitive fuzzy similarity measure with tendency. There are many methods for calculating the similarity of intuitionistic fuzzy sets. This paper adopts the similarity measurement method of intuitionistic fuzzy sets with tendency. The similarity calculation formula of two intuitionistic fuzzy sets $P_1=\langle \alpha_1,\beta_1,\pi_1\rangle$ and $P_2=\langle \alpha_2,\beta_2,\pi_2\rangle$ is as follows:

$$S(P_1,P_2)=1-\omega(\left|\alpha_i-\alpha_j\right|+\left|\beta_i-\beta_j\right|)-a\left|S(i)-S(j)\right|-b\left|S'(i)-S'(j)\right| \tag{5}$$

Among them $S(i)=\alpha_i-\beta_i$, $S'(i)=(\alpha_i+\alpha_i\pi_i)-(\beta_i+\beta_i\pi_i)$ and $\omega+a+b=\frac{1}{2}$. The above formula can be used to calculate the similarity of the tendency of the intuitionistic fuzzy set.

2.1. Intuitionistic fuzzy set transformation method based on sentiment dictionary

After defining the intuitionistic fuzzy set expression and calculation of perceived recommendation trust, the next step is to convert the objective recommendation information into intuitionistic fuzzy sets. This paper adopts a method based on sentiment dictionary to realize the conversion from text to numerical value, in which the method used is SnowNLP.

SnowNLP is a natural language processing method and a powerful Python library for Chinese text processing that can easily process Chinese text content. The library includes Chinese word segmentation, part-of-speech tagging, sentiment analysis, text classification, keyword/abstract extraction, TF-IDF, text similarity and other functions. SnowNLP supports hidden Markov models, naive Bayes, TextRank and other methods, and can be widely used in text processing tasks. Its main principle is to use the built-in Dalian University of Technology sentiment dictionary to calculate the sentiment score of the text to represent the probability of semantic tendency. SnowNLP is based on a probabilistic statistical model and has good support for Chinese corpus, especially for processing unstructured Chinese text data.

2.2. Density-based clustering methods

Density-based clustering methods can handle clusters of arbitrary shapes. The Density-Based Spatial Clustering of Application with Noise (DBSCAN) method is a typical density-based clustering method. It defines a cluster as the largest set of density-connected points, can divide areas with sufficient density into clusters, and can find clusters of arbitrary shapes in noisy spatial data sets. Before performing DBSCAN clustering, two parameters need to be clarified: the neighborhood radius of the core point e and Density threshold of $MinPts$. Where e is expressed as the neighborhood distance threshold of a certain sample, and $MinPts$ is expressed as e the threshold of the number of samples in the neighborhood of a certain sample with a distance of. According to the two hyperparameters of DBSCAN, some relevant definitions of DBSCAN are given:

Definition 1 (e-neighborhood): For $p_j \in P_{X_{i1}}$, its e-neighborhood contains the sub-sample sets in the sample set $P_{X_{i1}} p_j$ whose distance from is not greater than e, that is $N \in (P_{X_i}) = \left\{ p_j \in P_{X_i} \mid \text{distance}(p_i, p_j) \le e \right\}$, the number of this sub-sample set is recorded as $\left| N \in (P_{X_i}) \right|$.

Definition 2 (core object): For any sample $p_j \in P_{X_i}$, if its e-neighborhood corresponds to $\left| N \in (P_{X_i}) \right|$ at least $MinPts$ samples, that is, if $\left| N \in (P_{X_i}) \right| \ge MinPts$, it p_j is a core object.

Definition 3 (Density Direct Access): If p_i it is located p_j in the -neighborhood of and p_j is ϵa core object, it is called p_i from p_j density direct access.

Definition 4 (density reachable): For p_i and p_j, if there exists a sample sequence $p_1, p_2, \cdots p_t$ that satisfies $p_i = p_1$, $p_t = p_j$, and is directly reachable p_{t+1} by p_t density, then it is called p_j density p_i reachable. In other words, density reachability satisfies transitivity. At this time, all transitive samples in the sequence $p_1, p_2, \cdots p_{t-1}$ are core objects, because only core objects can make other samples directly reachable by density.

Definition 5 (density connected): For p_i and p_j, if there exists a core object sample p_h such that p_i and p_j are both p_h reachable by density, then p_i and are said to be p_j density connected.

searches for high data density areas of a data set e by looking at the neighborhood radius of each object. If e the number of objects in the neighborhood radius of a data object exceeds $MinPts$ the density threshold, the data object is used as the core object of the newly formed cluster. DBSCAN repeatedly looks for objects that can be directly density-reachable by these core objects and marks these data objects as a class. When no new data objects can be added to any cluster, data objects without categories are marked as noise points, and the clustering process ends.

2.3. DBSCAN parameter processing method

The clustering results of DBSCAN are seriously affected e by $MinPts$ the two parameters and many early studies adopted manual selection methods for the selection of the two parameters. There is also a parameter selection method for the traditional DBSCAN e method that is determined by k-dist sorting the curve in descending order, and the curve change threshold point determined by the maximum curvature point, that is, the inflection point, is used as e a parameter. This is also a commonly used method for adaptive parameter selection in current research. By drawing a descending k-dist graph of the data, appropriate e values are selected, and then the values are confirmed according to the data form $MinPts$ to ensure that good results are achieved in distance. k-dist The specific process of drawing the graph is as follows:

1) Choose a distance metric: First, you need to choose a distance metric to calculate the distance between data points. Usually, Euclidean distance is used, but other distance metrics can also be selected according to the characteristics of the data.

2) Select k value: Determine the size of k value, usually choose a suitable value between 2 and the square root of the number of data points. This k value will be used to calculate the distance of each data point to its first k nearest neighbors.

3) Calculate k-dist the value: For each data point, calculate its distance to the first k nearest neighbors and arrange these distances in descending order. These distances will form k-dist the vertical axis of the graph.

4) Draw k-dist a graph: Use the data point index as the horizontal axis and the values in descending order k-dist as the vertical axis to draw a graph in the coordinate system k-dist.

5) Analyze k-dist the graph: Analyze k-dist the graph and try to find an inflection point or a location where the curve changes significantly. k-dist The value corresponding to this location is usually considered to be an appropriate e value.

6) Select e value: According to k-dist the analysis results of the graph, select a suitable e value as the parameter of DBSCAN.

MinPts selection method is $MinPts = \dim + 1$, where $\dim$ is the dimension of the data to be clustered. However, this method also has disadvantages. Since the DBSCAN method is mainly used for multidimensional data clustering, it will $MinPts$ set the value to a fixed value, reducing the consistency of the parameter with the data set. As the characteristics of the data set change, it cannot have a corresponding change trend, resulting in errors in the number of generated clusters and the amount of noise.

2.4. Clustering effect evaluation indicators

After clustering is completed, you need to select appropriate indicators to judge the clustering effect. In addition to judging the effect based on the clustering image, there are also the following common indicators for judging the clustering effect:

1) Silhouette Coefficient. The silhouette coefficient is an indicator used to evaluate the quality of clustering, which takes into account both the compactness and separation of clustering. It measures the density and separation of clustering results by calculating the ratio of the average distance of a sample to samples of the same category and the average distance of samples of different categories. The value range of the silhouette coefficient is between [-1, 1]. If the silhouette coefficient is close to 1, it means that the samples are well clustered, and the distance within the cluster is much larger than the distance between clusters; if the silhouette coefficient is close to 0, it means that the compactness and separation of the sample clustering are close, and the sample may be on the boundary of the cluster; if the silhouette coefficient is close to -1, it means that the sample clustering effect is not good, and the sample is more likely to be incorrectly assigned to an adjacent cluster. Therefore, a higher silhouette coefficient usually indicates a more reasonable clustering result. The silhouette coefficient can be applied to various clustering methods, and is often used in combination with other evaluation indicators to select the optimal number of clusters or evaluate the quality of clustering.

2) DBI Index. The DBI (Davies-Bouldin Index) index is an indicator used to evaluate the performance of clustering methods. It takes into account the compactness and separation of clusters. The DBI

index measures the compactness and separation of clusters by calculating the average similarity between different clusters and the sample similarity within a cluster. The lower the index value, the better the clustering result.

3) Intuitive fuzziness bias. Intuition Fuzzy Index (IFI) is an indicator used to evaluate the fuzziness of clustering results. It can measure the fuzziness of clustering results, that is, the fuzziness of samples between different clusters. The smaller the IFI index, the clearer the clustering results are and the clearer the belonging of samples between different clusters. Conversely, the more ambiguous the clustering results are. The value range of IFI index is between 0 and 1. Generally, the closer to 0, the clearer the clustering results are, and the closer to 1, the more ambiguous the clustering results are.

4) Intuitive fuzzy partition entropy. Intuition Fuzzy Partition Entropy (IFPE) is an indicator used to evaluate the fuzziness of clustering results. It is similar to the traditional entropy indicator, but is specifically defined for fuzzy clustering results. The IFPE index evaluates the degree of fuzziness by measuring the distribution of clusters in the clustering results. Generally, the value range of the IFPE index is from 0 to positive infinity. The closer it is to 0, the clearer the clustering result, and the closer it is to positive infinity, the more ambiguous the clustering result. The larger the IFPE index, the more ambiguous the clustering result, that is, the more uneven the distribution between clusters, and the less clear the belonging relationship of the samples; and the smaller the IFPE index, the clearer the clustering result, the more even the distribution between clusters, and the clearer the belonging relationship of the samples.

By using these indicators to evaluate clustering results, we can better understand the effect and quality of clustering, and then choose the best clustering method, adjust parameters or determine the optimal number of clusters. At the same time, these indicators can also help compare the effect differences of different clustering methods, so as to better perform clustering analysis on the data.

2.5. Summary of research methods

This chapter mainly introduces the relevant theories and methods involved in building a trust conflict aggregation model for perceptual recommendation. First, the basic operations of intuitionistic fuzzy sets and their transformation methods are introduced in detail. Secondly, the clustering methods used in this paper are explained, including DBSCAN and the distance measurement method k-dist curve method, and the judgment indicators of clustering results are introduced. Next, the research content carried out through the above theoretical methods will be described in detail.

3. Transformation method of intuitive fuzzy sets for patient-perceived recommendation trust

Patients obtain recommendation information on the Internet medical platform and process it subjectively, converting it into perceived recommendation trust, which constitutes a trust transfer process. In this process, different areas of the cerebral cortex form trust tendencies and distrust tendencies, respectively, leading to patients forming multi-dimensional perceived recommendation trust. Therefore, this paper uses intuitionistic fuzzy sets to describe patients' perceived trust, converting a large amount of objective recommendation information into patients' subjective and differentiated perceived recommendation trust intuitionistic fuzzy sets, highlighting the subjectivity of the human brain in the processing process.

3.1. Analysis of Factors Influencing Perceived Recommendation Trust

Patients' trust in doctors is a complex psychological process, which is not only influenced by doctors' professional skills, communication skills and professional ethics, but also deeply influenced by the emotional recommendation information shared by other patients through Internet medical platforms. In the digital age, evaluation and feedback on Internet medical platforms have become key factors affecting patients' trust. Positive recommendation information can significantly improve patients' trust in doctors, while negative evaluations may cause doubts and even lead to loss of trust.

From a psychological perspective, patients' trust in doctors contains deep emotional needs. According to Maslow's hierarchy of needs theory, these needs can be divided into belonging and love needs and respect needs. The belonging needs involve the psychological state of being accepted, loved, encouraged and supported. Especially in doctor-patient communication, facing the uncertainty of the disease, patients often feel anxious and fearful, and are eager to relieve this psychological pressure by obtaining more information about doctors. This need is particularly strong when facing serious medical decisions such as serious illness or surgery, and patients tend to choose doctors who are considered more credible. Therefore, the emotionally inclined recommendation information of other patients has a decisive influence on patients who are worried and fearful.

In addition, as social creatures, humans' desire for emotions permeates all social interactions, including the process of establishing trust between doctors and patients. Therefore, converting recommendation information based on emotional tendencies into patients' perceived recommendation trust is not only innovative in theory, but also provides insights into how to establish and maintain a trusting relationship between doctors and patients in practice. In this process, recognizing and utilizing the power of emotional factors plays a vital role in promoting effective communication between doctors and patients, enhancing patient satisfaction, and improving the quality of medical services.

3.2. Perception Recommendation Trust Intuitionistic Fuzzy Set Transformation Process

In the field of Internet medicine, the recommendation information provided by other patients is the main basis for new patients to establish trust in doctors. The emotional tendency expressed in these recommendation information directly affects the level of trust. This paper combines the intuitive fuzzy set with the text sentiment analysis method to calculate the emotional tendency of the recommendation information provided by other patients, involving three dimensions. By redistributing the emotional tendency and forming a new intuitive fuzzy set, it is possible to transform objective recommendation information into the patient's subjective perceived recommendation trust.

At the same time, in order to make the transformation and subsequent model construction more in line with the research background, the following assumptions are made about the "Internet + Medical Health" service environment:

1) Information validity assumption: When considering the model development of Internet information and comments, it is necessary to consider and clarify the assumption that it is valid under the conditions of the Internet medical service environment, that is, the data obtained from the Internet medical service platform is real and valid, and there is no situation where there are fake reviews or false comments, which may require the establishment of different trust mechanisms.

2) Patient behavior pattern assumption: It is assumed that patients are "irrational people" when using Internet medical services. Each patient will have different initial trust in risks based on the severity of their illness. At the same time, in the "Internet + Medical Health" service process, different doctors are medical plans, and patients make decisions from these doctors. Each doctor may have different results for different patients, and each result can be composed of a perceived recommendation trust value and a probability weight.

After completing the confirmation of the method and the assumptions about the service background of "Internet + Healthcare", the specific transformation process will be introduced below.

3.2.1 Recommendation Information and Representation of Perceived Recommendation Trust Intuitionistic Fuzzy Sets. Assuming that the patient has browsed a total of n doctors in a certain department on the Internet medical platform, the doctor set is represented by $X=\{X_1,X_2,\cdots,X_i,\cdots,X_n\}$, where represents X_i the th doctor $i=1,2,\cdots,n$ browsed by the patient in the department, i. The patient's perceived recommendation trust in the doctor $P=\langle\alpha,\beta\rangle$ is represented by an intuitive fuzzy set, α where represents the patient's trust in the doctor's attribute information, represents the patient β's distrust of the doctor's attribute information, and π represents the patient's hesitation about the doctor's attribute information. Assuming that the th i doctor has a total m of items of perceived recommendation trust, the intuitive fuzzy set of the doctor's perceived recommendation trust is $P_{X_i}=\{p_1,p_2,\cdots,p_j,\cdots,p_m\}$, where represents the th p_j item of perceived recommendation trust $j=1,2,\cdots,m$ of the doctor, j.

3.2.2. Emotional Recognition of Objective Recommendation Information. After completing the hypothesis of the research problem, it is necessary to calculate the specific value of perceived recommendation trust. However, the objective recommendation information of the Internet medical platform is mostly text information, which cannot be directly used to calculate the patient's trust. Therefore, this paper uses a sentiment dictionary to realize the transformation of objective text to perceived recommendation trust intuitive fuzzy set. According to the SnowNLP method, the text sentiment is statistically analyzed, and the sentiment score of the comment text is statistically analyzed through the built-in Dalian University of Technology sentiment dictionary. The sentiment tendency contained in the comment is used to represent the patient's trust tendency. The positive, negative and neutral sentiment tendencies in the comment text correspond to the three-dimensional data of the intuitive fuzzy set. The specific calculation formula is as follows:

Taking the perceived recommendation trust of the th doctor j assumed in the previous article as an example, the i th recommendation information is identified according to the division of word polarity by the Dalian University of Technology Sentiment Dictionary to identify the three sets of sentiment words contained in it:

The positive sentiment word set is expressed as: $\{x_j^{\text{positive}} \mid x_j^{\text{positive}_1}, x_j^{\text{positive}_2}, \cdots\cdots\}$.

The negative sentiment word set is expressed as: $\{x_j^{\text{negative}} \mid x_j^{\text{negative}_1}, x_j^{\text{negative}_2}, \cdots\cdots\}$.

The neutral sentiment word set is represented as: $\{x_j^{\text{neutral}} \mid x_j^{\text{neutral}_1}, x_j^{\text{neutral}_2}, \cdots\cdots\}$.

After completing the identification of the sentiment words contained in each recommendation text, the next step will be to further analyze and quantify the patients' perceived recommendation trust based on the scores of the positive, negative, and neutral sentiment word sets contained in the Dalian University of Technology Sentiment Dictionary.

3.2.3. Calculating the perceived recommendation trust intuitionistic fuzzy set based on text sentiment score. SnowNLP 's sentiment score is calculated by statistically analyzing the sentiment words in the text. Specifically, SnowNLP uses a sentiment dictionary to perform sentiment analysis on the text, and then calculates the sentiment score of the text based on the number and sentiment polarity of the sentiment words in the text. This article calculates the sentiment score of each word set based on the TF-IDF value of each sentiment word in the overall review data to represent the number of words, and the strength score of each sentiment word in the dictionary to represent the sentiment polarity:

The formula for calculating the positive sentiment score is:

$$S_{x_j^{\text{positive}}}=\sum S_{x_j^{\text{positive}}}^{\text{TF-IDF}}\times S_{x_j^{\text{positive}}}^{\text{Affective polarity}} \tag{6}$$

The negative sentiment score calculation formula is:

$$S_{x_j^{\text{negative}}}=\sum S_{x_j^{\text{negative}}}^{\text{TF-IDF}}\times S_{x_j^{\text{negative}}}^{\text{Affective polarity}} \tag{7}$$

The formula for calculating the neutral sentiment score is:

$$S_{x_j^{\text{neutral}}} = \sum S_{x_j^{\text{neutral}}}^{\text{TF-IDF}} \times S_{x_j^{\text{neutral}}}^{\text{Affective polarity}} \tag{8}$$

Normalize the three sentiment scores:

$$S_j^{\text{positive}} = \frac{S_{x_j^{\text{positive}}}}{S_{x_j^{\text{positive}}} + S_{x_j^{\text{negative}}} + S_{x_j^{\text{neutral}}}} \tag{9}$$

$$S_j^{\text{negative}} = \frac{S_{x_j^{\text{negative}}}}{S_{x_j^{\text{positive}}} + S_{x_j^{\text{negative}}} + S_{x_j^{\text{neutral}}}} \tag{10}$$

$$S_j^{\text{neutral}} = \frac{S_{x_j^{\text{neutral}}}}{S_{x_j^{\text{positive}}} + S_{x_j^{\text{negative}}} + S_{x_j^{\text{neutral}}}} \tag{11}$$

The three sentiment scores are used to replace the trust tendency of the review, and x_j the intuitive fuzzy set of review-aware recommendation trust is obtained:

$$P_{X_j} = \langle \alpha_j, \beta_j, \pi_j \rangle = \langle S_j^{\text{positive}}, S_j^{\text{negative}}, S_j^{\text{neutral}} \rangle \tag{12}$$

Then i the intuitive fuzzy set of the perceived recommendation trust of the doctor is:

$$P_{X_i} = \left\langle P_{x_1}, P_{x_2}, \cdots, P_{x_j}, \cdots, P_{x_m} \right\rangle \tag{13}$$

3.2.4. Perception - recommendation-trust conversion process. The complete doctor perception recommendation trust intuitive fuzzy set transformation experimental process is given below:

Input: n Past patient review texts of doctors X (the number of reviews for each doctor is m), where i the review text of the th doctor is represented as $X_i = \{x_1, x_2, \cdots\cdots, x_m\}$.

Output: n Intuitive fuzzy sets of doctors' perceived recommendation trust $P_X = \left\{P_{X_1}, P_{X_2}, \cdots, P_{X_i}, \cdots, P_{X_n}\right\}$.

experiment process:

Step 1: Identify all sentiment words in the comments based on the Dalian University of Technology sentiment dictionary built into Snow NLP and divide the word polarity.

Step 2: According to formulas (6)-(11), based on the intensity score of the identified sentiment word and the TF-IDF value of the word, calculate the sentiment score of the corresponding category.

Step 3: Normalize the three types of sentiment scores according to formula (12) and output them as intuitive fuzzy sets of perceived recommendation trust in the form of formula (13).

4. A clustering method considering patients' perceived trust tendency in recommendation

This chapter will conduct a clustering study on the massive objective recommendation information in Internet medical care. Since the objective recommendation information in Internet medical care is massive, the converted intuitive fuzzy set of perceived recommendation trust is also massive, so clustering is needed to reflect the human brain's simplification process of massive information. How to cluster the massive perceived recommendation trust is the main problem to be solved in Chapter 3 of this article.

4.1. Construction of Perceptual Recommendation Trust Clustering Method

After converting objective text data into subjective perceptual recommendation trust intuitive fuzzy sets in Chapter 3, the perceptual recommendation trust intuitive fuzzy sets of each doctor based on comments can be obtained. In the actual application of Internet medical platforms, each doctor usually generates corresponding perceptual recommendation trust intuitive fuzzy sets based on hundreds to thousands of comments. If there are hundreds of doctors in the same department of the "Internet + Medical Health" service platform, the number of comments that need to be processed will reach millions. Since these massive comment recommendation data may greatly increase the complexity of trust calculation, after reading a large amount of recommended information, patients cannot have an impression of each one, but cluster information with similar tendencies into one category, and simplify a large amount of information into several categories of impressions with obviously different tendencies. This simplification process is suitable for simulation by clustering methods. Therefore, this paper proposes a method to use clustering methods to simulate the simplification process of the human brain in data processing.

Specifically, this study improves the distance measurement method in the DBSCAN clustering method to better handle the characteristics of intuitive fuzzy sets of perceived recommendation trust. Through the improved method, the sets in the dataset can be effectively assigned to different clusters, ensuring that the tendency of perceived recommendation trust between different clusters is clearly distinguished.

4.1.1. Analysis of the distribution of perceived recommendation trust data. Before performing cluster analysis of intuitive fuzzy sets of perceived recommendation trust, it is necessary to select an appropriate method based on the relevant characteristics of the data. Intuitive fuzzy sets are composed of three-dimensional intuitive fuzzy numbers, which show obvious coplanar characteristics in space. For example: an intuitive fuzzy number can be expressed as a triple (x, y, z), satisfying the condition $x + y + z = 1$, where z can be determined by membership x and non-membership y, so that all intuitive fuzzy numbers in three-dimensional space only exist on the equilateral triangle plane $z = 1 - x - y$ formed by the three points (1,0,0), (0,1,0), (0,0,1). Take the perceived recommendation trust data of Dr. Xu Shaopeng transformed in the previous article as an example, as shown in the following Figure 1:

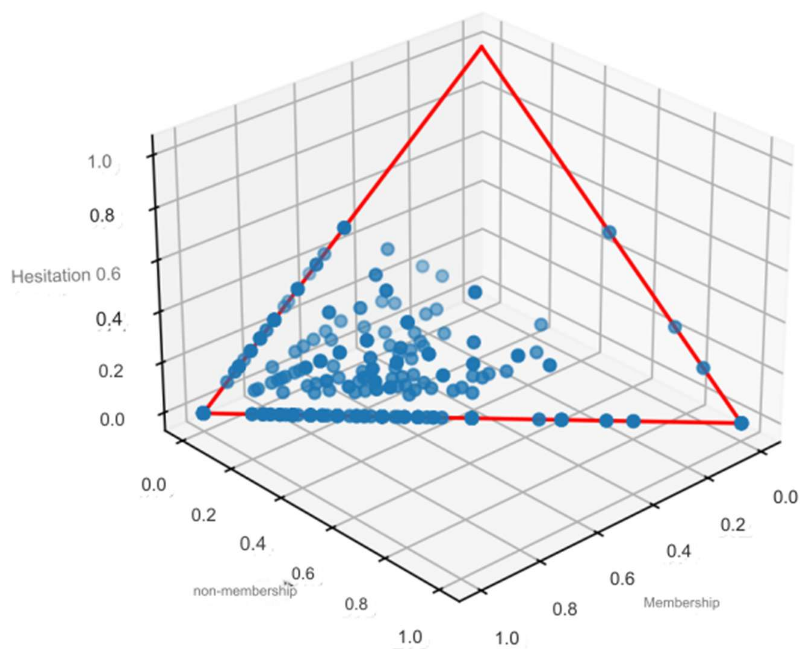

Fig. 1. Three-dimensional spatial distribution of doctor Xu Shaopeng's perceived recommendation trust intuitive fuzzy set data

From the image, we can find that the intuitionistic fuzzy number, as a three-dimensional data, has a very obvious coplanar feature. Map the intuitionistic fuzzy set and redraw the two-dimensional plane image of the coplanar area (see Figure 2):

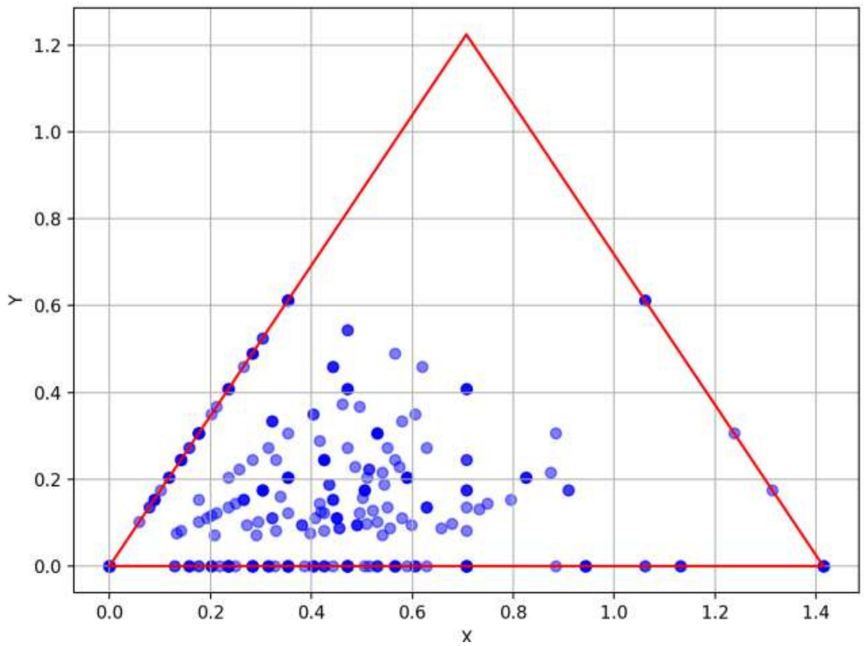

Fig. 2. Two-dimensional plane diagram of doctor Xu Shaopeng's perceived recommendation trust intuitive fuzzy set data

All the intuitionistic fuzzy numbers fall $(0,0),(\sqrt{2},0),\left(\frac{\sqrt{2}}{2},\frac{\sqrt{6}}{2}\right)$ within the equilateral triangle area established by three vertices, where the center of the triangle represents the situation where the membership, non-membership and hesitation are equal. In this triangular area, the distribution of the perceived recommendation trust density shows obvious unevenness, including dense and sparse areas. In addition, the trust tendency of the data is significantly affected by the vertices of the triangle: for example, the intuitive fuzzy numbers near the triangle vertex (0,0) are perceived by patients to have a stronger trust tendency. Therefore, the problem of clustering the intuitive fuzzy sets of perceived recommendation trust is actually a clustering problem involving multi-dimensional coplanar data with multiple densities and heavy perceptions. When choosing a clustering method, it should be considered that the method can handle such a complex data structure and effectively identify and distinguish different trust tendency dense areas.

In order to solve the perceptual recommendation trust clustering problem mentioned above, this paper uses DBSCAN to cluster the data. DBSCAN is a density-based clustering method that describes the compactness of the sample set based on a set of neighborhoods, and describes the compactness of the sample distribution in the neighborhood through parameters $(e, MinPts)$. e The e value is used to control the number of points that will fall in the neighborhood of the core object. The larger the value, the fewer the number of categories. Conversely, the e smaller the value, $MinPts$ the more the number of categories. $MinPts$ The value controls the number of core objects in the neighborhood of the core object. The smaller the value, the fewer the number of categories, and vice versa. The DBSCAN method is particularly suitable for processing data with uneven density because they can effectively identify clusters with different densities and do not require the number of clusters to be specified in advance.

Since the neighborhood distance calculation formula commonly used in the DBSCAN method is the Euclidean distance, the distance cannot reflect the tendency of perceived recommendation trust. Therefore, this paper proposes a tendency-aware intuitive fuzzy set similarity measurement method in the context of Internet medical care to improve the DBSCAN distance calculation method, and then clusters the DBSCAN clustering based on data density in order to better cluster the perceived recommendation trust intuitive fuzzy set.

4.1.2. Tendency-aware Recommendation Trust Intuitive Fuzzy Set Distance Measurement Method. From the intuitionistic fuzzy set data distribution in the figure above, doctors' perceived recommendation trust has a very obvious tendency. Taking Dr. Xu Shaopeng as an example, his perceived recommendation trust is mostly concentrated in the area of tendency trust. Different doctors will have different data distribution tendencies, so this tendency needs to be taken into account when calculating the distance metric.

The tendency of perceived recommendation trust is seriously affected by the vertices. By calculating the distance between the data point and the three vertices of the equilateral triangle, the tendency of the data to the three trust situations is reflected. The shorter the distance, the greater the proportion of the tendency. Assuming that the three vertex intuitive fuzzy sets are represented by p_A, p_B, p_C, the distance from the perceived recommendation trust i to the three vertices is calculated by the Euclidean distance formula as follows:

$$d_{iD} = \sqrt{(p_i - p_D)^2}, D = A, B, C \tag{14}$$

The tendency matrix of perceived recommendation trust is expressed as:

$$\begin{bmatrix} d_{1A} & d_{1B} & d_{1C} \\ d_{2A} & d_{2B} & d_{2C} \\ d_{3A} & d_{3B} & d_{3C} \\ \vdots & \vdots & \vdots \\ d_{mA} & d_{mC} & d_{mC} \end{bmatrix} \tag{15}$$

Assume that the trust tendency coefficient is Q_A, the distrust tendency coefficient is Q_B, and the hesitation tendency coefficient is Q_C. Now we use statistical methods to calculate the three trust tendency coefficients:

$$Q_D = 1 - \frac{1}{m}\sum_{i=1}^{m} d_{iD} \tag{16}$$

Normalize the three coefficients:

$$Q'_D = \frac{Q_D}{2\sum Q_D} \tag{17}$$

Then the three coefficients calculated in the above formula are improved into formula (5), and the trust similarity of recommendation with tendency perception is obtained: Q

$$S(p_i, p_j) = 1 - Q'_c(|\alpha_i - \alpha_j| + |\beta_i - \beta_j|) - Q'_A|S(i) - S(j)| - Q'_B|S'(i) - S'(j)| \tag{18}$$

the two perceived recommendation trusts through the above similarity, we can get the distance $D(p_i, p_j)$ with tendency, which is expressed as:

$$\begin{aligned} D(p_i, p_j) &= 1 - S(p_i, p_j) \\ &= Q'_c(|\alpha_i - \alpha_j| + |\beta_i - \beta_j|) - Q'_A|S(i) - S(j)| - Q'_B|S'(i) - S'(j)| \end{aligned} \tag{19}$$

According to the above formula, the perceptual recommendation trust distance matrix with tendency is calculated D as:

$$D=\begin{bmatrix} D(p_1,p_1) & D(p_1,p_2) & \cdots & D(p_1,p_{\mathrm{m}}) \\ D(p_2,p_1) & D(p_2,p_2) & \cdots & D(p_2,p_{\mathrm{m}}) \\ D(p_3,p_1) & D(p_3,p_2) & \cdots & D(p_3,p_{\mathrm{m}}) \\ \vdots & \cdots & & \cdots \\ D(p_m,p_1) & D(p_m,p_2) & \cdots & D(p_m,p_{\mathrm{m}}) \end{bmatrix} \tag{20}$$

4.2. Description of DBSCAN clustering method based on perception recommendation trust tendency

After completing the new distance measurement, DBCSCAN clustering is now performed on the intuitive fuzzy set of perceived recommendation trust. In this paper, the perceptual recommendation trust distance matrix with tendency is used D as the distance to draw a descending k-dist graph, and then the value of the best clustering situation is determined according to the inflection point method e. Assuming that there is m an intuitive fuzzy set sample represented by $P_{X_i}=\{p_1,p_2,\cdots,p_j,\cdots,p_m\}$ the DBSCAN clustering method based on the perceptual recommendation trust tendency, the specific calculation process is described as follows:

Input: Samples of intuitive fuzzy sets of perceived recommendation trust $P_{X_i}=\{p_1,p_2,\cdots,p_j,\cdots,p_m\}$;

Distance matrix D, density threshold $MinPts$.

Output: Perception recommendation trust intuitive fuzzy set sample point cluster label:

Step 1: Recommend the trust distance matrix based on the improved perception D as the distance distribution matrix.

Step 2: Sort the elements of each row in ascending order D.

Step 3: Calculate the average value of the column of $k(1\le k\le m)$ the sorted matrix to obtain the D k-dist value, and sort the calculated k-dist values from small to large. Plot the sorted k-dist values into a curve graph in the coordinate system. The horizontal axis is the data point index, and the vertical axis is the corresponding k-dist value. Draw a descending k-dist graph.

Step 4: According to the inflection point method, observe whether there is an obvious inflection point in the K -dis t graph or a position where the curve changes significantly. The distance of the inflection point position is used as e a parameter.

Step 5: Set a suitable density threshold $MinPts$ and start looking for core points: traverse all sample points $P_{X_i}=\{p_1,p_2,\cdots,p_j,\cdots,p_m\}$ and calculate $|N\in(P_{X_i})|$, if $|N\in(P_{X_i})|\ge MinPts$, then $\Omega=\Omega\cup\{X_i\}$.

Step 6: Starting from any core point that has not been visited, find the clusters generated by samples that are density-reachable, until all core points are visited, and output the cluster divisions.

5. Example Experiment

In order to verify the transformation and clustering methods proposed in this paper, the experimental data of this paper were selected from the top seventeen recommended doctors in the coronary heart disease department of the "Haodaifu Online" platform (https://www.haodf.com/citiao/jibing-guanxinbing/tuijian-doctor.html).

5.1. Perception Recommendation Trust Conversion Analysis Experiment

The rationale for selecting these physicians as research subjects involved three main aspects:
1) Platform perspective: We chose "Good Doctor Online" as the data source mainly because it is a leading platform in China's Internet medical and health services, with rich doctor resources and a huge patient case database. The data obtained from this platform is not only authentic and reliable, but also highly representative.

2) Disease perspective: Coronary heart disease is one of the most common chronic diseases in my country, with a high prevalence. Doctors in the coronary heart disease department were selected as the research subjects because early medical intervention can effectively control the disease and relieve symptoms, while delayed treatment may lead to serious consequences, including death. Therefore, this patient group is in a high-risk decision-making environment, which is consistent with the setting of the patient's medical environment in this study.

3) Information acquisition perspective: The top 17 doctors were selected based on the fact that doctors with higher rankings usually gain more attention and trust from patients, thus providing more stable research data. This selection helps to collect feedback information from patients with a high degree of trust and sense of security (see Figure 3).

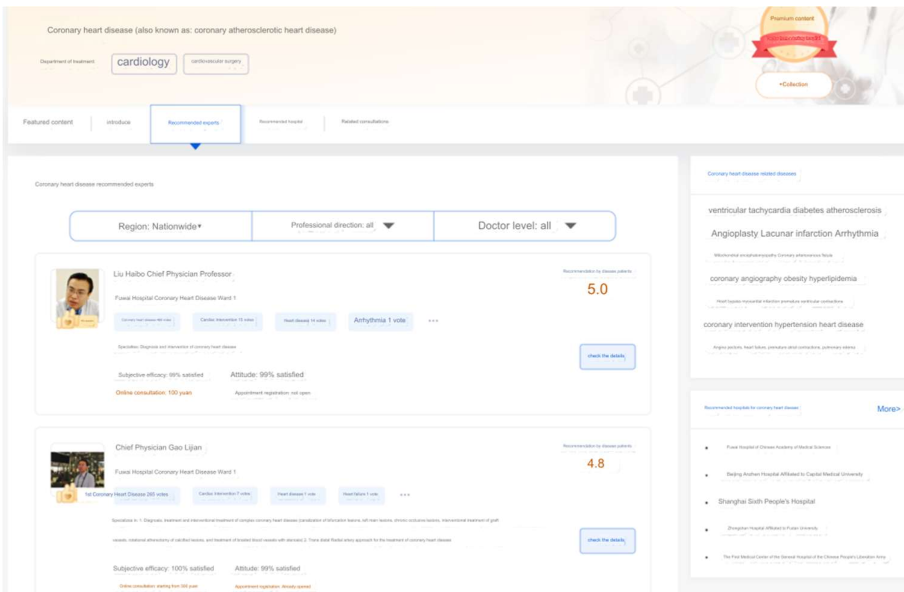

Fig. 3. Ranking of doctors' recommendations in the coronary heart disease department of the Good Doctor Online platform (Screenshot source: Good Doctor Online Coronary Heart Disease Department)

Through the above method flow, the objective text is converted into an intuitive fuzzy set, realizing the transformation of objective recommendation information into subjective patient perceived recommendation trust. The research data in this paper uses the real comment data of the top 17 doctors in the coronary heart disease department crawled by the Good Doctor Online Platform - a total of 10,670 patient comments, and the specific data is as follows Table 1:

Table 1. Top 17 doctors in the coronary heart disease department and number of comments

Serial number	doctor	Number of reviews
1	Liu Haibo	1000
2	Gao Lijian	888
3	Zhang Ming	788
4	Wang Qi	1000
5	Shen Congxing	995
6	Xu Shaopeng	617
7	Zhang Jing	1001
8	Zhang Yin	472
9	Kim Hyun	314
10	Yao Kang	417

11	Zhang Baohai	255
12	Gao Yuxia	863
13	Nie Honggang	490
14	Feng Xuyang	355
15	Zheng Bin	104
16	Cui Cheng	111
17	Luo Chucheng	1000

Through Python programming and Dalian University of Technology's sentiment dictionary, we identify the three types of sentiment words in the comments: positive, neutral, and negative. Then we use SnowNLP programming to calculate the sentiment score, and then normalize the sentiment score to get the initial perception recommendation trust intuitive fuzzy set of the corresponding doctor. Taking the comment data of Dr. Xu Shaopeng as an example, the following is the real data conversion (see Figure 4).

Fig. 4. Data crawling of Dr. Xu Shaopeng's comments

When analyzing the conversion effect of the recommendation texts processed by the method, it was observed that the method can clearly identify the perceptual recommendation trust with tendency, and reasonably convert and score it. Specifically, text 1 is the patient's positive recommendation information, showing a high degree of membership and a low degree of non-membership and hesitation, which shows that the model can accurately capture the patient's positive feedback on the doctor's treatment effect. Text 2 is also positive recommendation information, but the recommendation information it contains is not as much as that provided by text 1. Therefore, although it also shows a high degree of membership and a low degree of non-membership and hesitation, the degree of membership is not as good as that of text 1. For text 3, the recommendation information tendency is not as high as the previous two. Therefore, after the conversion, although the degree of membership is also high and the degree of non-membership is low, the degree of hesitation is high, which reflects that the patient still has some hesitation while giving positive feedback. In text 4, since the patient still showed discomfort symptoms after treatment and failed to provide clear positive feedback, a high degree of non-membership and hesitation was given in its intuitive fuzzy set, which effectively revealed the patient's dissatisfaction and uncertain psychological state. The membership and non-membership degrees in text 5 are higher, and the hesitation is more average, indicating that the model accurately captures the patient's objective recommendation on the doctor's treatment effect (see Table 2).

Table 2. Conversion of some of Dr. Xu Shaopeng's recommendation texts into intuitionistic fuzzy sets

Serial number	text	Membership	Non-membership	Hesitation
1	Two blood vessels were blocked. Director Xu performed two operations with superb medical skills. Both were successful. Although the patient was 86 years old, he was out in 40 minutes. Director Xu has high medical ethics, is enthusiastic, patient and meticulous with patients, and answers all questions, making the patient very clear about the precautions for postoperative care. Just 9 days after the second operation, he can already walk every day and his physical strength has recovered well. Thank you Director Xu! Thank you Director Xu's team!	0.81174949	0	0.18825051
2	Director Xu understood the patient's family's anxiety and arranged the surgery in time.	0.495353399	0.223636413	0.281010188
3	Myocardial infarction I was hospitalized for emergency interventional treatment, took medicine on time as prescribed by the doctor, and had follow-up checkups on schedule. I feel fine. Thank you, Director.	0.461638693	0.152621679	0.385739627
4	Sudden myocardial infarction, one week after stent surgery, occasional shortness of breath, general weakness	0	0.555238578	0.444761422
5	The proximal middle part of the lad was severely blocked, the operation time was short, and the patient was discharged from the hospital in three days.	0.346068162	0.301258546	0.352673292

This research method verifies the effectiveness of this method by transforming the text data of Dr. Xu Shaopeng. This work is repeated in the online comment texts of other doctors, and the intuitive fuzzy sets of perceived recommendation trust of the top 17 other doctors in the coronary heart disease department can be obtained.

5.2. Perception recommendation trust intuitive fuzzy clustering experiment

In order to test the effectiveness and performance of the method in this chapter, this chapter continues to use the data of Dr. Xu Shaopeng as an example, conducts tests through Python programming, and finally compares the result indicators of this method with the DBSCAN method.

5.2.1. Results of intuitive fuzzy clustering of perceived recommendation trust considering patients' trust tendency. This paper uses Python programming to calculate the doctor's perceived recommendation trust tendency. According to formulas (14) - (17), the trust tendency coefficient of Dr. Xu Shaopeng is calculated as $\Phi = 0.21$, the distrust tendency coefficient is $\Psi = 0.15$, and the hesitation tendency coefficient is $\varpi = 0.14$. According to formulas (18) - (20), the perceived recommendation trust intuitive fuzzy set distance matrix with tendency is calculated. At the same time, in order to make the data present a clear separation and aggregation pattern, considering the characteristics and distribution of the data, the k value is selected as 3 to draw the k -dist graph. The specific results are as follows (see Figure 5):

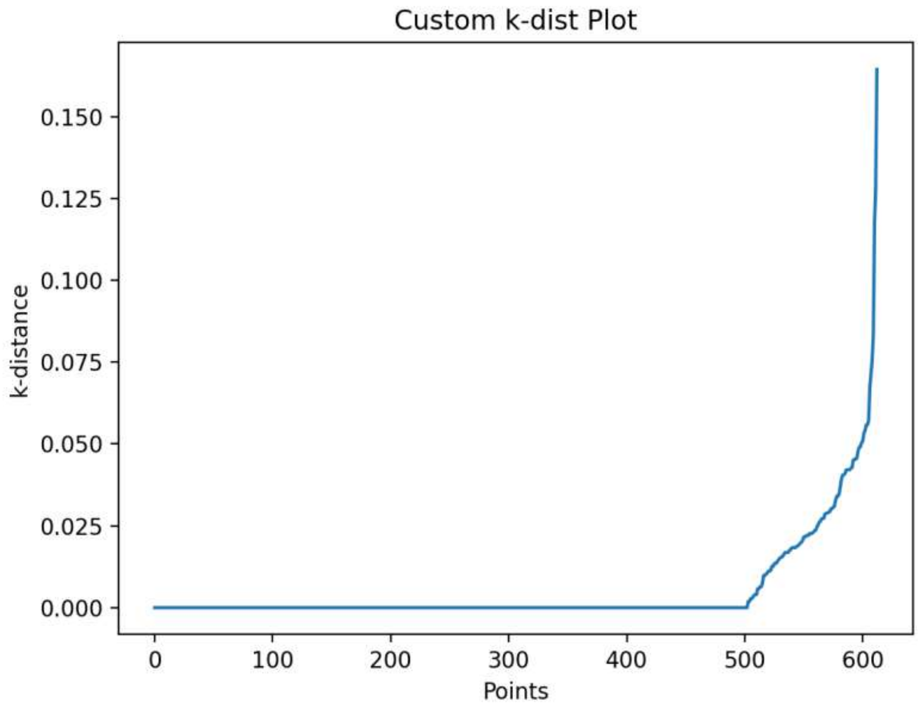

Fig. 5. Dr. Xu Shaopeng's perceived recommendation trust k -dis t diagram

At this time, the e value of the inflection point is 0.1644, and then the MinPts value is set to 10 to obtain the intuitive fuzzy clustering results of Dr. Xu Shaopeng's perceived recommendation trust as shown in the following Figure 6:

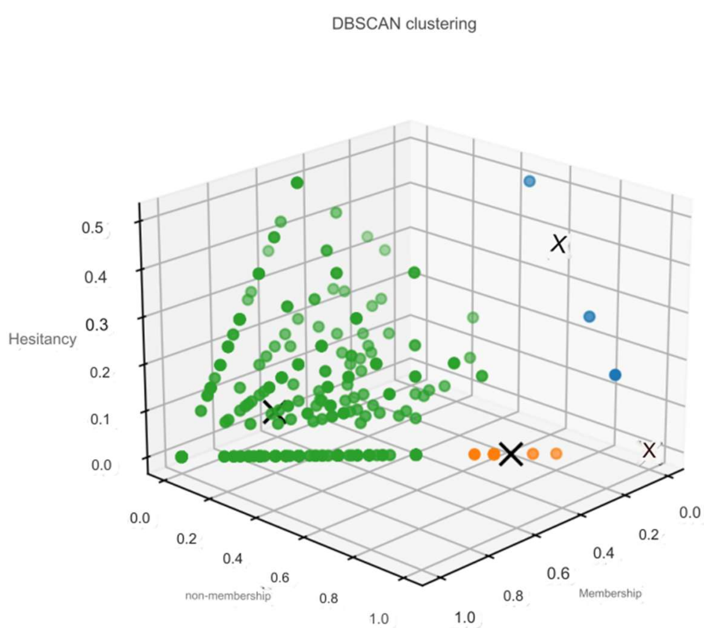

Fig. 6. 3D image of the trust clustering results of Dr. Xu Shaopeng's perceived recommendation

The above experimental results show that when the recommendation trust clustering model perceived by Dr. Xu Shaopeng shows the best effect, the number of clusters is 4. Under this setting, the specific cluster center and the number of perceived recommendation trust within the cluster are as follows Table 3:

Table 3. Clustering results of doctor Xu Shaopeng's perceived recommendation trust

Clustering	Cluster Center	quantity
Cluster 1	[0, 0.62142857, 0.37857143]	5
Cluster 2	[0.29833333, 0.70166667, 0]	15
Cluster 3	[0.76124121, 0.15858621, 0.08017258]	583
Cluster 4	[0, 1, 0]	10

The results of cluster analysis show that the 617 intuitive fuzzy sets of perceived recommendation trust of the doctor can be effectively divided into four different clusters. The number of intuitive fuzzy sets contained in these clusters are 5, 15, 583 and 10 respectively, showing different perceived recommendation trust tendencies.

Specifically, cluster 1 contains 5 intuitionistic fuzzy sets, and the cluster centers of its perceived recommendation trust intuitionistic fuzzy sets are located at <0, 0.62142857, 0.37857143>. This shows that the perceived recommendation trust belonging to this category mainly tends to be distrustful, accompanied by a relatively high degree of hesitation. This hesitation result shows that this type of patients have a high degree of uncertainty about the doctor's ability or service. This trust result reflects that this type of patients have formed an attitude of distrust towards doctors after being influenced by the comments on the online platform. Although there are obvious doubts pointing to the potential disadvantages of doctors, the patients' perceived recommendation trust attitude is not completely inclined to distrust, and the hesitation component reveals the patients' caution and uncertainty when making the final judgment.

Cluster 2 consists of 15 intuitionistic fuzzy sets, and its cluster center is represented as <0.29833333, 0.70166667, 0>, where the hesitation is zero, indicating that the perceived recommendation trust in this cluster shows obvious polarity, that is, the perception of trust and distrust is relatively high, and uncertainty is almost non-existent. This data feature shows that after receiving the recommendation information, the patient can form a clear attitude and can clearly recognize the advantages and disadvantages of the doctor. Despite the existence of trust, the patient's overall perception of the doctor still tends to be less trusting. This expresses an important phenomenon. Even if the patient can recognize some of the doctor's advantages, this is not enough to completely offset their perception of the doctor's disadvantages, thereby affecting the final trust judgment.

Cluster 3 is the cluster with the largest number of intuitionistic fuzzy sets, totaling 583. The cluster center of the perceived recommendation trust of this cluster is located at <0.76124121, 0.15858621, 0.08017258>. The hesitation degree of this cluster center is 0.08017258, which is relatively low, while the trust membership is significantly higher, indicating that patients can form a more certain sense of trust after receiving the recommendation information. This high trust membership clearly indicates that the patient's perceived recommendation trust is mainly biased towards trust. It can be reflected that most patients have a consistent positive evaluation of the doctor and trust establishment. The high trust membership indicates that most patients believe that the doctor's ability and service meet or exceed their expectations, thereby strengthening their trust in the doctor.

Cluster 4 consists of 10 intuitionistic fuzzy sets, and its cluster center coordinates are <0, 1, 0>, indicating that in this cluster, the hesitation is zero, the trust non-membership is extremely high, and there is no hesitation. This shows that this cluster represents an extreme distrust tendency of perceived recommendation trust, which typically reflects the perceived recommendation trust formed by patients based on negative evaluations of doctors. Such a clear distrustful attitude may be due to the patient's obvious dissatisfaction with the doctor's treatment effect or service attitude.

The clusters that tend to trust contain the most intuitive fuzzy sets, while the clusters that tend to distrust and hesitate contain fewer. This research result is consistent with the general trend of perceived trust generated by comments recommended by other patients in Internet medical services. In actual situations, positive reviews are often more than negative reviews. Judging from the centers of various clusters and the number of samples included in the above clustering results, the method proposed in this study can effectively group perceived recommendation trust into clusters with obvious distinction and conflict. This shows that the method proposed in this paper is effective in identifying and distinguishing patients' trust attitudes towards medical services. Next, this paper will compare the clustering effect of this study with other existing methods through comparative analysis to further verify the superiority and applicability of this method.

5.2.2 Clustering effect evaluation. Under the same parameter conditions, this paper uses the DBSCAN method (i.e., the traditional method) without improved distance measurement to cluster the data of Dr. Xu Shaopeng to compare the robustness and superiority of the model in this study. Specifically, we use the Euclidean distance as the clustering distance of the DBSCAN method, set the e value to 0.1644, and the MinPts value to 5. Under this setting, the DBSCAN method clusters Dr. Xu Shaopeng's perceived recommendation trust into 18 clusters (as shown in Figure 7).

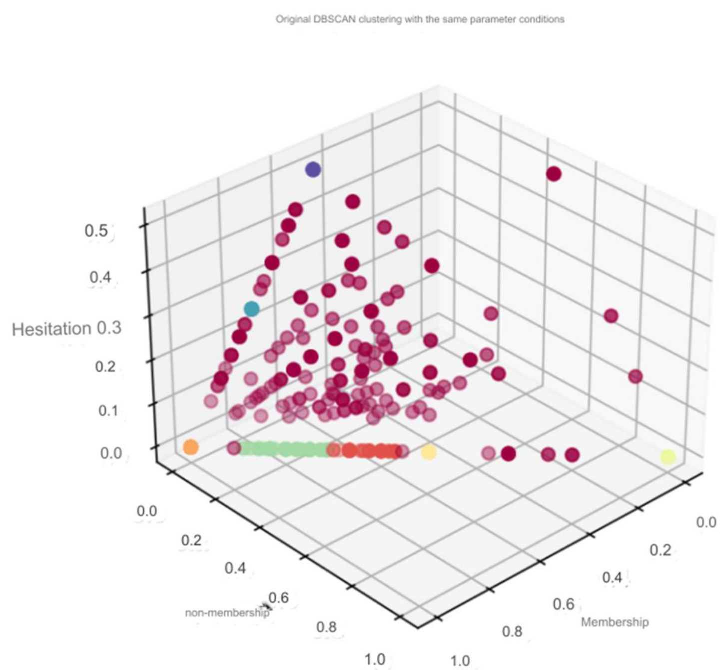

Fig. 7. Three-dimensional image of the original DBSCAN clustering results under the same parameter conditions

Compared with the clustering results of this paper, the traditional method divides the data too finely. This excessive segmentation destroys the tendency of perceived recommendation trust, resulting in disorganized clustering results and overfitting problems. At the same time, too many clusters lead to poor interpretability of clustering results. Relatively speaking, the clustering method proposed in this paper shows higher robustness while keeping the data tendency clear.

At the same time, in order to verify the superiority of the method in this paper, the silhouette coefficient, Davies-Bouldin index, intuitionistic fuzzy deviation, and intuitionistic fuzzy partition entropy of the method in this paper and the original DBSCAN clustering results are compared respectively. The results are shown in the following Table 4:

Table 4. Comparison of clustering results of different models

Clustering methods	SC	DBI	IFI	IFPE
DBSCAN	0.4568	2.1859	0.0228	1.8054
Methods of this paper	0.4833	0.5061	0.1611	0.2057

It can be found that except for the IFI coefficient, the clustering results of this method are better. At the same time, the IFI coefficient is not much different from DBSCAN. The reason why it is larger than the other is that the original DBSCAN divides the perceived recommendation trust into more classes under the same parameter conditions, and each class is divided into smaller classes. However, the actual situation can be seen from the image that the division of this method is more reasonable. Therefore, it is believed that the method of this paper has superiority in dealing with the intuitive fuzzy clustering of perceived recommendation trust in the context of Internet medical care.

6. Conclusion

Studies the problem of perceived recommendation trust in Internet medical care where patients have a tendency to trust, conducts an in-depth analysis of the characteristics of patients' perceived recommendation trust and trust transmission, proposes a research idea of " conversion first, then clustering ", and constructs a perceived recommendation trust clustering method based on intuitive fuzzy sets. The research content mainly includes two parts:

1) In the trust transfer stage, in view of the ambiguity of patients' perceived recommendation trust, intuitive fuzzy sets are used to characterize patients' perceived recommendation trust. According to the emotional tendency of patients' recommendation information, objective recommendation information is transformed into patients' subjective perceived recommendation trust, which reflects the subjectivity and ambiguity of perceived trust. Through five sets of data analysis, the different transformation results and rules of intuitive fuzzy sets of perceived recommendation trust are verified, and the influence of different text emotional tendencies on perceived recommendation trust is verified.

2) In the clustering stage, considering the high density and small-scale massive recommendation information of Internet medical care, and the problem that trust tendency and perceived recommendation trust cannot be clustered simultaneously, three trust tendency coefficients are calculated from the data distribution to improve the perceived recommendation trust distance metric, and a perceived recommendation trust clustering method that considers the influence of trust tendency is constructed. The robustness and superiority of this method are proved through data experiments.

The clustering method proposed in this paper can cluster the recommendation information while considering the patient's trust tendency, so as to better characterize the subjectivity of the patient's perceived recommendation trust. The clustering method proposed in this paper can adapt to the Internet medical environment with large scale, massive user-generated content and strong dynamics, and provide a new perspective for the analysis of patient trust orientation in platform measurement. In future research work, we will consider clustering methods of perceived recommendation trust under more subjective conditions. In the uncertain decision-making environment, the phenomenon that patients have higher perceived risks and therefore negative opinions may be more influential is also incorporated into the clustering method, so as to construct and improve the calculation method system of patient perceived recommendation trust in the context of " Internet + medical health" services.

Funding

This work was supported by National Natural Science Foundation of China Youth Project (72001184): Perceptual Trust transfer model of Internet Medical Service based on Intuitionistic Fuzzy sets. And also supported by Youth Project of Fujian Provincial Natural Science Foundation (2021J05264): Research on the perceived Trust transfer model of the elderly on Internet + Medical and health Services.

References

[1] Wu, H., & Lu, N. (2017). Online written consultation, telephone consultation and offline appointment: an examination of the channel effect in online health communities. International Journal of Medical Informatics, 107, 107-119.

[2] Lu, Y., & Wang, Q. (2022, July). Doctors' preferences in the selection of patients in online medical consultations: an empirical study with doctor–patient consultation data. In Healthcare (Vol. 10, No. 8, p. 1435). MDPI.

[3] Yang, M., Jiang, J., Cameron, A. F., & Liu, X. (2023). How do you cope? Online medical consultation service uncertainty, coping strategies, and subsequent payment. Electronic Commerce Research and Applications, 61, 101294.

[4] Jiang, J., Cameron, A. F., & Yang, M. (2020). Analysis of massive online medical consultation service data to understand physicians' economic return: Observational data mining study. JMIR medical informatics, 8(2), e16765.

[5] Zhao, W., Liu, Q. B., Guo, X., Wu, T., & Kumar, S. (2022). Quid pro quo in online medical consultation? Investigating the effects of small monetary gifts from patients. Production and Operations Management, 31(4), 1698-1718.

[6] Xing, W., Hsu, P. Y., Chang, Y. W., & Shiau, W. L. (2020). How does online doctor–patient interaction affect online consultation and offline medical treatment?. Industrial Management & Data Systems, 120(1), 196-214.

[7] Chen, M., Liu, X., Zhang, J., Sun, G., Gao, Y., Shi, Y., ... & Qi, H. (2020). Characteristics of online medical care consultation for pregnant women during the COVID-19 outbreak: cross-sectional study. BMJ open, 10(11), e043461.

[8] He, Y., Guo, X., Wu, T., & Vogel, D. (2022). The effect of interactive factors on online health consultation review deviation: An empirical investigation. International Journal of Medical Informatics, 163, 104781.

[9] Zhao, X., & Mao, Y. (2021). Trust me, I am a doctor: Discourse of trustworthiness by Chinese doctors in online medical consultation. Health communication, 36(3), 372-380.

[10] Cao, B., Huang, W., Chao, N., Yang, G., & Luo, N. (2022). Patient activeness during online medical consultation in China: multilevel analysis. Journal of Medical Internet Research, 24(5), e35557.

[11] Yang, Y., Zhang, X., & Lee, P. K. (2019). Improving the effectiveness of online healthcare platforms: An empirical study with multi-period patient-doctor consultation data. International Journal of Production Economics, 207, 70-80.

[12] Wan, Y., Peng, Z., Wang, Y., Zhang, Y., Gao, J., & Ma, B. (2021). Influencing factors and mechanism of doctor consultation volume on online medical consultation platforms based on physician review analysis. Internet research, 31(6), 2055-2075.

[13] Zhou, F., Wang, Z., Mai, X., Liu, X., Reid, C., Sandover, S., ... & Xu, D. (2020). Online clinical consultation as a utility tool for managing medical crisis during a pandemic: retrospective analysis on the characteristics of online clinical consultations during the COVID-19 pandemic. Journal of Primary Care & Community Health, 11, 2150132720975517.

[14] Jiang, H., Mi, Z., & Xu, W. (2024). Online Medical Consultation Service–Oriented Recommendations: Systematic Review. Journal of Medical Internet Research, 26, e46073.

[15] Zhang, Y. (2021). How doctors do things with empathy in online medical consultations in China: A discourse-analytic approach. Health communication, 36(7), 816-825.

[16] Shen, T., Li, Y., & Chen, X. (2024, August). A Systematic Review of Online Medical Consultation Research. In Healthcare (Vol. 12, No. 17, p. 1687). MDPI.

[17] Mao, Y., & Zhao, X. (2019). I am a doctor, and here is my proof: Chinese doctors' identity constructed on the online medical consultation websites. Health Communication, 34(13), 1645-1652.

[18] Singh, A. P., Joshi, H. S., Singh, A., Agarwal, M., & Kaur, P. (2018). Online medical consultation: a review. International Journal of Community Medicine and Public Health, 5(4), 1230-1232.

[19] Jiang, J., Yang, M., Kiang, M., & Cameron, A. F. (2021). Exploring the freemium business model for online medical consultation services in China. Information Processing & Management, 58(3), 102515.

[20] Almathami, H. K. Y., Win, K. T., & Vlahu-Gjorgievska, E. (2020). Barriers and facilitators that influence telemedicine-based, real-time, online consultation at patients' homes: systematic literature review. Journal of medical Internet research, 22(2), e16407.

[21] Chang, Y. W., Hsu, P. Y., Wang, Y., & Chang, P. Y. (2019). Integration of online and offline health services: The role of doctor-patient online interaction. Patient Education and Counseling, 102(10), 1905-1910.

[22] Peng, Y., Yin, P., Deng, Z., & Wang, R. (2020). Patient–physician interaction and trust in online health community: the role of perceived usefulness of health information and services. International Journal of Environmental Research and Public Health, 17(1), 139.

[23] Hu, Y., Wang, J., Zhou, J., Gu, Y., Nicholas, S., & Maitland, E. (2024). Preferences of Individuals With Obesity for Online Medical Consultation in Different Demand Scenarios: Discrete Choice Experiments. Journal of Medical Internet Research, 26, e53140.

[24] Fu, Y., Tang, T., Long, J., Lin, B., Li, J., Quan, G., ... & Shi, L. (2021). Factors associated with using the internet for medical information based on the doctor-patient trust model: a cross-sectional study. BMC Health Services Research, 21, 1-9.