Computers in Biology and Medicine 109 (2019) 138–147

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

Hospital evaluation mechanism based on mobile health for IoT system in social networks

Jia Wu[a,b,*], Xiaoming Tian[c,**], Yanlin Tan[d]

[a] School of computer science and engineering, Central South University, Changsha, Hunan, 410083, China
[b] "Mobile Health" Ministry of Education-China Mobile Joint Laboratory, Changsha, 410083, China
[c] Hunan Forest Botanical Garden, Changsha, 410075, China
[d] PET-CT Center, The Second Xiangya Hospital of Central South University, Changsha, 410083, China

ARTICLE INFO

Keywords:
Hospital evaluation
Trust model
Eigenvalue
Social network
Big data

ABSTRACT

The uneven distribution of medical resources is a serious problem in developing countries. Those seeking timely treatment have difficulty choosing the right hospital. To found sustainable development with medical system, this paper establishes a model of the hospital confidence evaluation index by combining national evaluation and a third-party evaluation. The model is applied to a social network. Users from any region can use the model through APP in IoT, a hospital analysis index query, which selects the best hospital for diagnosis and treatment. The model can locate different personnel characteristics by modifying the control variables. Establishing a medical system with big data provides good model characteristics. Effective data analysis through large data users in the sample is established to provide the most effective hospital recommendation, which is a good solution to the selectivity problem. The contributions in this works are: (1) Models of initial trust and hospital evaluations are established by combining national and third-party assessments; (2) the initial trust evaluation model is modified and optimized by establishing control variables; (3) the trust evaluation mechanism of users in social networks is obtained through big data sampling and model analysis, and the balanced distribution of the medical staff is realized.

1. Introduction

Life, in developing countries, cannot be protected by medicine because the medical technology is underdeveloped and the population is large. One of the result is that patients with light illness may get serious even cause a disastrous infection. Finally developing countries have to spend a great amount of personnel and finance to solve the problem.

Many developing countries in Asia and Africa, health of people may not be protected by medicine, because of huge population and underdevelopment medical technology [1,2]. The SARS virus and the Ebola virus broke out in Asia and Africa, more than thousands of people lose their life. If patients can obtain treatment and epidemic disease can be controlled in those areas, more people can keep their life [3–8].

Some developing countries such as China and India which have over one billion people may face the biggest problem is population and medical resource imbalance. In China, a super city such as Beijing, has over 20 million workers and 10 million children and the aged. Only no more than 3000 doctors can medical health service. Unfortunately, those doctors must solve hundreds of pathological reports which come from thousands of kilometers, because advanced medical devices and excellent doctors are centralized in super cities and advanced hospitals. Over more, some reports and pathological sections may be a big challenge, the question 'malignant tumor or not' may wait for advanced hospitals and doctors answered [9–15]. For all patients, how to select suitable hospital is also a problem. How many patients must be waited for a doctor? Patients may have not enough security [16–20].

Fig. 1 reflects the uneven distribution of medical, population, and land resources in China. Limited medical resources are mainly distributed in large cities and developed areas. The population of these cities and hospitals is 300 million. Only 7% of the population receives 80% of medical resources, and 93% only receives 20% less of the medical resources.

The development of mobile Internet eases the imbalance in the distribution of medical resources through online medical appointment registrations and counseling. However, many people still choose to go to the city with good hospitals when they need surgery or have

* Corresponding author. School of computer science and engineering, Central South University, Changsha, Hunan, 410083, China.
** Corresponding author.
E-mail addresses: jiawu5110@163.com (J. Wu), tianxiaoming1986@126.com (X. Tian).

https://doi.org/10.1016/j.compbiomed.2019.04.021
Received 3 January 2019; Received in revised form 10 February 2019; Accepted 20 April 2019
0010-4825/ © 2019 Elsevier Ltd. All rights reserved.

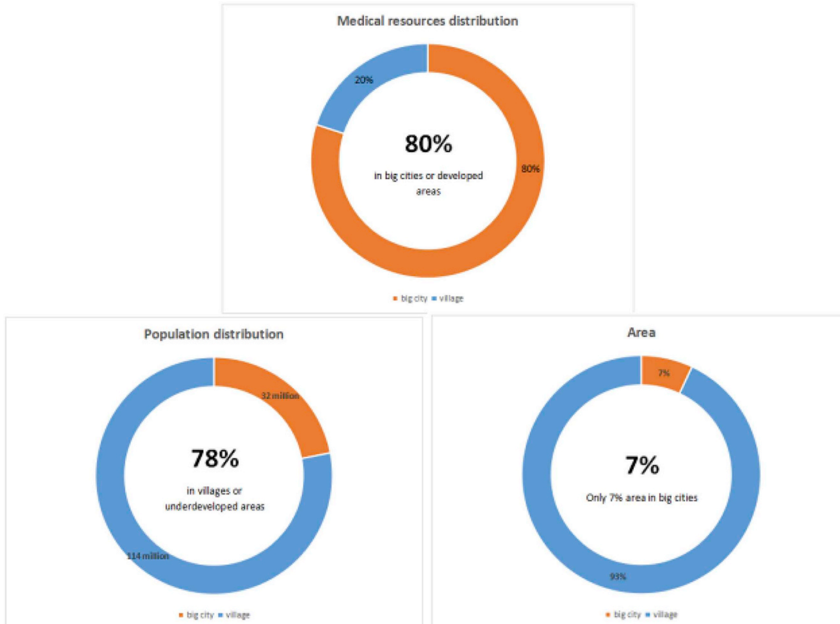

Fig. 1. Distribution of medical, population, and land resources in China.

incurable diseases. This situation does not only exacerbate the difficulty of large hospitals but also makes these hospitals lose the opportunity to assume medical responsibility [21–23].

Fig. 2 shows the authoritative and third-party data in evaluating the seven state hospitals. Fig. 2 shows that the results of national statistics and third-party data have a significant difference, because medical technology is better at large hospitals. The limited number of medical resources is due to the number of patients. Consequently, patients receive less care from hospitals, which seriously affects the confidence of patients. Moreover, several patients wait for treatment for a long period of time, which greatly impacts the reputation of hospitals. Fig. 2 also shows that clear guidance is difficult for patients or users, regardless of the data released by authorities or the third party [24,25].

In fact, many judgments and diagnosis reports could be analyzed by medical devices. Doctors can make a decision by their experience after reports supported. All reports can be transmitted by mobile devices, patients can select different APP devices and read those reports.

However, in developing counties, we must face some embarrassed.

(1) high misdiagnosis rate between doctors and patients carry social contradiction. Many families start doubting excessive consumption coming from doctors' conclusion.
(2) many repetitive works may affect doctors, such as similarity diagnosis reports, images, biochemical indices, can increase high misdiagnosis rate by doctors.
(3) no effective evidences or conclusions can acquire confidence

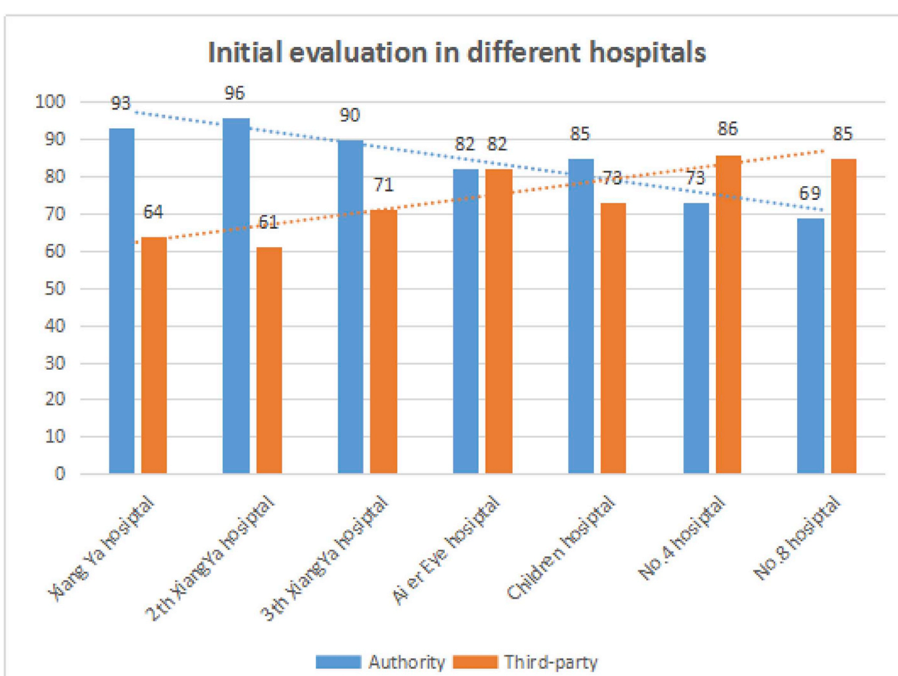

Fig. 2. Authority and third-party data.

between patients and doctors, because patients can not know complicated indices.

How to give an effective evidence and improve high misdiagnosis rate in developing countries when we faced big data population.

The development of evaluation medical system in developing countries may create good results. With medical resources and evaluation medical system, doctors can make decision analysis. The probability of acquiring sick assists doctors or decision making. In the light of decision system in medical treatment, the features can be applied in IoT system, hospitals, patients, and doctor would combine a communication medical system. This system does not only quickly provide messages to patients, but also reduces the pressure of obtaining resources. According to evaluation medical system, patients could know the conclusions by medical system. It could improve many social contradictions between doctors and patients.

This paper aims to address these problems. An evaluation method is proposed based on trust mechanism of mobile medical hospitals. This method is applied to the user evaluation mechanism of social networks in IoT system. The hospital evaluation model was established by analyzing authoritative institutions and third-party joint data. Users objectively evaluate hospitals through wireless communication, and the iterative transmission situation updates in real time to provide users with the most timely and optimal evaluation of hospital data. Thus, patients can enter hospitals based on rational choices according to the data. Consequently, people making rational choices can avoid crowding at hospitals make the rational allocation of medical resources possible.

The contributions of this paper are as follows.

(1) Models of initial trust and hospital evaluations are established by combining national and third-party assessments.
(2) The initial trust evaluation model is modified and optimized by establishing control variables.
(3) The trust evaluation mechanism of users in social networks is obtained through big data sampling and model analysis, and the balanced distribution of the medical staff is realized.

2. Related works

Many works in medical device in IoT have become research hotspots in the medical treatment field.

Literature [7] suggests a system data model in medical data and IoT system. The resource-based data accessing method (UDA-IoT) can be designed to acquire the IoT data and then improve data resources. This medical system may explain IoT-based system in emergency medical services and demonstrate how to collect or interoperate IoT data and then support to emergency medical services. The result explains resource-based IoT data system can be effective in heterogeneous data environment and support data accessing timely in medical system.

Literature [8] shows a knowledge-based access medical system. It can conclude two parts. One is the heuristic approach to enhance. It used to pseudo relevance method for more effective query expansion, even if expanding queries boosting the similarity score. The other is how to improve the retrieval performance with knowledge-based. It can explain a relevance model based on tensor factorization which can identify semantic association patterns in sparse settings. All data and patterns are used as inference paths in knowledge-based query expansion and copy to medical information retrieval.

Literature [9] proposed a framework in IoT evaluation system. It used natural language processing and then analyzed clinical notes readmission. In this system, many methods can be adopted in the field of data mining and machine learning. This framework is created and selected the best components while maintaining fast computational times in medical environment.

Literature [10] discusses the discrete event system specification in medical system engineering. It can develop coordination models in transactions that involve multiple disparate activities and then it needs to be selectively sequenced to coordinated care interventions. This system shows how such coordination concepts provide the layers and support the proposed information in healthcare as a learning collaborative system.

In literature [11] addresses an organ-centric compositional medical system. In this model, medical devices in IoT can be composed into clusters and then created organ-specific physiology in system manner. The organ-centric brings device in many patterns of sensing and then control human physiology. The organ-centric architectural patterns can enable rapid and composition of supervisory controllers in medical scenarios.

In the literature [12] proposes a low-complexity coordination protocol for networked in medical access system. The suggestion architecture organizes in a hierarchical and then reminder the manner in accordance to human physiology. It avoids potential conflicts and useless controls, when efficient concurrent in medical devices.

3. Methods

This paper considers the special situation of medical services and divides the initial trust of consumers in mobile medical services into four aspects: hospital and individual characteristics, structure assurance, and information quality. People may have initially trusted in mobile health care services before actually using them. They may also have high initial trust in mobile health care services if they recognize that the hospitals that provide them are reputable. Thus, establishing a model for hospital evaluation is needed to provide users with the most suitable hospital.

3.1. Eigenvalue design of initial trust model

Hospital evaluation usually includes two levels. First is the level of recognition of national institutions, which is the main evaluation of a hospital. The level of a hospital is comprehensively assessed by the national organization of strict medical institutions, and the results are published on an authorized website. Comprehensive and professional rankings provide precise hospital positions.

Second is the public comments of patients and their families on the comprehensive evaluation of services of hospitals through the authorized third-party evaluation. These evaluations reflect the possible service problems of hospitals.

The two dimensions of the evaluation of weight indicator eigenvalues should be identified to calculate the initial trust and facilitate the design of the model.

(1) Evaluation model of national authoritative institutions

The evaluation model of the national human rights institution includes three parts: legal and technical structure guarantees, and information release quality. The model is defined as follows.

Definition 1. Legal structure guarantee reflects the implementation of hospitals and management structure in the law, policy, and other aspects of execution and completion. Each year, hospitals in China follow the structure of the review. The corresponding score is according to the assessment results published on the Ministry of Health (MOH) and the website of provincial health department. This indicator is important for the implementation of health care reforms in hospitals.

Assuming T years, the legal structure of a hospital to ensure the score for $s_l^{(k)}$and the weight of$H_l$is computed as follows:

$$H_l = s_l^{(k)} \times \frac{s_l^{(k)}}{s_l^{(k-1)}} \tag{1}$$

Where$s_l^{(k-1)}$indicates the rating of the hospital from the previous year. Equation (1) measures the pace of implementation of the policy and reform of a hospital every year.

Definition 2. Technical structure assurance reflects the personnel, equipment, technology, and other aspects pertaining to the ability of the performance of a hospital. A hospital can effectively treat patients through surgery, medication, and rehabilitation training. This indicator is the most important. The government strictly inspects the indicator each year. The hospitals are randomly examined and given a corresponding score.

$\varepsilon^{(t)}$denotes the number of random checks made by the government each year, and $s_r^{(t)}$is the first sampling of t scores. The first year of the technical structure is measured to ensure the weight of$H_s^{(t)}$, as shown in the following:

$$H_s^{(t)} = \frac{1}{\varepsilon^{(t)}} \sum_{r=1}^{N} s_r^{(t)} \tag{2}$$

The guarantee weight$H_s$of the technical structure for hospitals is:

$$H_s = \frac{1}{N} \sum_{i=1}^{N} H_s^{(t_i)} = \frac{1}{N} \sum_{i=1}^{N} \sum_{r=1}^{N} s_r^{(t_i)} \times \frac{1}{\varepsilon^{(t_i)}} \tag{3}$$

where N indicates the number of years of participation in the assessment.

Definition 3. Information release quality indicates the accuracy, effectiveness, and timeliness of the information released by hospitals. The release of correct, effective, and timely information of a hospital through radio and wireless APP devices reminds people to prevent diseases from spreading, which can effectively reduce epidemics. Moreover, the hospital can provide information, such as the number of beds and the current number of their medical treatments. People can access information released by the hospital that year through their mobile devices.

The index has been listed as the annual national information. Reform focus on the assessment of indicators for the evaluation of hospital services is important. Authoritative institutions evaluate the pace of hospital information process yearly according to the information released by the hospital.

The quality of information released$H_q$mainly comprises three evaluation scores: correctness r_c, timeliness , and validity$r_e$of information. The value$H_q$of information distribution quality$\chi_i^T$is adjusted by setting the weight factor$i \subseteq [1,2,3]$, where T is the year. From this, the quality of the information publishedH_q can be defined as:

$$H_q = \chi_1^T \times r_c + \chi_2^T \times r_s + \chi_i^T \times r_e \tag{4}$$

The scores of hospitals can be computed by national agencies using Definitions 1 to 3. The national review weight$\widetilde{H}$can be obtained as follows:

$$\widetilde{H} = H_l + H_s + H_q \tag{5}$$

3.2. Third-party review

Another way to evaluate hospitals is through public comment. A comprehensive evaluation of the hospital can be conducted by a third party through peer assessment and user evaluation. These evaluations reflect the possible service problems of hospitals. From these, we can derive the following definition.

Definition 4. Hospital reputation weight expresses the evaluation index of hospital management system. The patients and their families evaluate the management system of the hospital, personnel level of business, and hospital cleanliness. This evaluation is conducted after patients end their treatment and are discharged from the hospital. The scores provide the hospital a good basis to improve the management of some loopholes and the form of information dissemination, making more people understand the management capabilities of the hospital. The existing hospital evaluation mechanism does not provide evaluation reference of hospitals.

Assuming the hospital reputation weight isH_r, $h_r^{(i)}$denotes each index of the reputation evaluation of the hospital, and$h_r^{(i)}$is the score corresponding to each index. For all$h_r^{(i)}$found$\{h_r^{(i)} | h_r^{(i)} = r_i, i \in N\}$, Nrepresents a natural number. If $\lambda_r^{(k)}$is used to express the impact factor of each parameter, the weight of hospital reputation weight$H_r$can be obtained as follows:

$$H_r = \sum_i h_r^{(i)} = \sum_{i=1}^{N} \sum_{k=1}^{i} \lambda_r^{(k)} \times r_i \tag{6}$$

Definition 5. User confidence weight indicates the subjective hospital preference of users. This indicator is usually obtained from colleagues of the patient who did a recommendation, influence of hospital advertisements, and waiting time for admissions. The first effect of hospital identity to users do not come from the direct influence on the hospital but through large-data environment. Accepting an effective decision of evaluation information has clear subjectivity.

Assuming the hospital reputation weight is H_c, $h_c^{(i)}$denotes each index of the reputation evaluation of the hospital, and$h_c^{(i)}$is the score corresponding to each index. For all $h_c^{(i)}$found$\{h_c^{(i)} | h_c^{(i)} = c_i, i \in N\}$, Nrepresents a natural number. If $\lambda_c^{(k)}$is used to express the impact factor of each parameter, the weight of hospital reputation weight$H_c$can be obtained as follows:

$$H_c = \sum_i h_c^{(i)} = \sum_{i=1}^{N} \sum_{k=1}^{i} \lambda_c^{(k)} \times c_i \tag{7}$$

From Equation (7), we can calculate the third party given the agency review weight$\hat{H}$:

$$\hat{H} = H_r + H_c \tag{8}$$

Through the five definitions above, we can calculate the hospital trust$H$of people:

$$H = \alpha \times \widetilde{H} + \beta \times \hat{H} \tag{9}$$

where$\alpha$and βdenote trust adjustment factors, which depend on the objectivity of the evaluation mechanism.

3.3. Control variables design

Hospital evaluation varies for different populations. Fig. 3 is the Control variable model. The educational and income levels, gender, age, and occupation of people determine their different characteristics in the initial evaluation of hospital trust. Humanization model may give patients suitable recommend. Establishing control variables$\varphi[K]$ensure that the hospital evaluation is fair and objective, thereby assessing the initial trust of a hospital well.

Simultaneously, $\varphi[K]$choice must also meet the current national population statistics of the basic law, and control variables in the parameters must reflect the characteristics of population distribution of the country.

Hospitals in China implement the real name system. These hospitals keep the electronic medical records of their patients, which notes the gender, age, education level, occupation, income, and history of disease. Income can be identified through a questionnaire and webmail to better evaluate the initial confidence of users in hospitals. The basic characteristics of the sampled population can be adjusted any time by controlling the variables, which is more objective for hospital confidence assessment.

However, the sampling of population equilibrium is difficult in social networks. The model given to the evaluation mechanism shows a

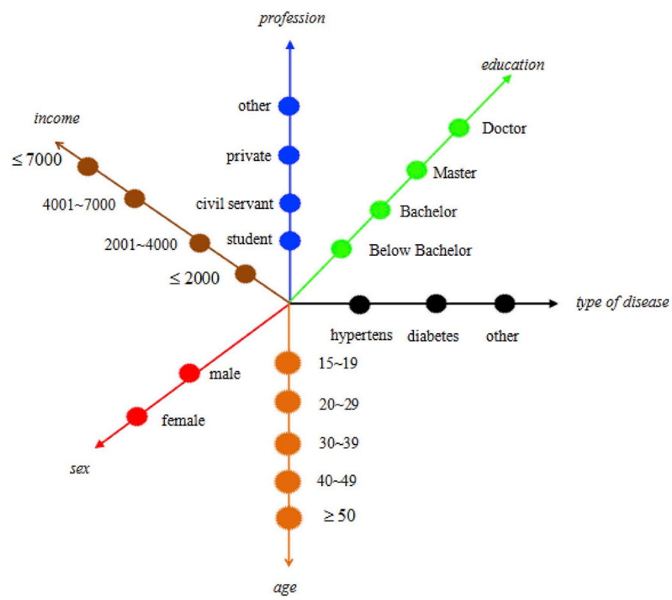

Fig. 3. Control variable model.$\varphi[K]$

prominent part of the age of sample. Finally, the results of the initial impartial evaluation of the hospital are obtained.

In this model, we can save and classify all data and then establish data base in different formats.

Numeric class: *age(int number); income(int number)*

Character class: *sex(chair); type of disease(chair); profession(chair); education(chair)*

We analyze the control variables to implement the equilibrium mechanism in social networks. Suppose $\varphi[K]$ represents the control variable adjustment factorA_{ij}. $A_{ij} = \frac{\dot{H}}{M_j}$, where $M_j$represents the total number of samples for each stratum.

3.4. Evaluating the transmission model

For a patient who needs to visit different places, finding a reliable hospital through mobile devices for medical treatment is the key to obtaining medical information. In social networks, the patient can be recommended at any time around the right hospitals based on the iterative evaluation mechanism of the method. Mobile devices, such as APP, provide a convenient environment for patients. Based on hospital service, patients can provide the quickest and most timely evaluation index in real time to make other users choose their preferred medical institutions.

Assuming that$\widetilde{q_i^n}$denotes time t in the evaluation score of the hospital, $A_{ij}$is the adjustment variable of the control variable, and $\widetilde{q_i^{n+1}}$denotes the hospital evaluation score of T+1 time. Thus,

$$\widetilde{q_i^{n+1}} = \widetilde{q_i^n} + \sum_j A_{ij}\widetilde{q_i^n} + \widetilde{H} \tag{10}$$

In T time, the evaluation index of hospital confidence can be expressed in an iterative way. The iterative process$\widetilde{q_i^n}$can be expressed as follows:

$$\widetilde{q_i^n} = \frac{\widetilde{q_i^n}}{\sum_j \widetilde{q_i^n}} \tag{11}$$

In T+1 time period, the evaluation index $\widetilde{q_i^{n+1}}$of hospital confidence is expressed as:

$$\widetilde{q_i^{n+1}} = \frac{\left. q_i^n + \widetilde{H} + \sum_j A_{ij} q_j^n \right]}{\sum_k \left[q_k^n + \widetilde{H} + \sum_j A_{kj} q_j^n \right]}, \quad \sum_i q_i^n = 1, \ q_i^0 = 1 \tag{12}$$

After several iterations, the evaluation result of the hospital is:

$$C_{cn}(v_i) = N \lim_{n\to\infty} q_i^n \tag{13}$$

The evaluation result can be reflected in the APP at each moment

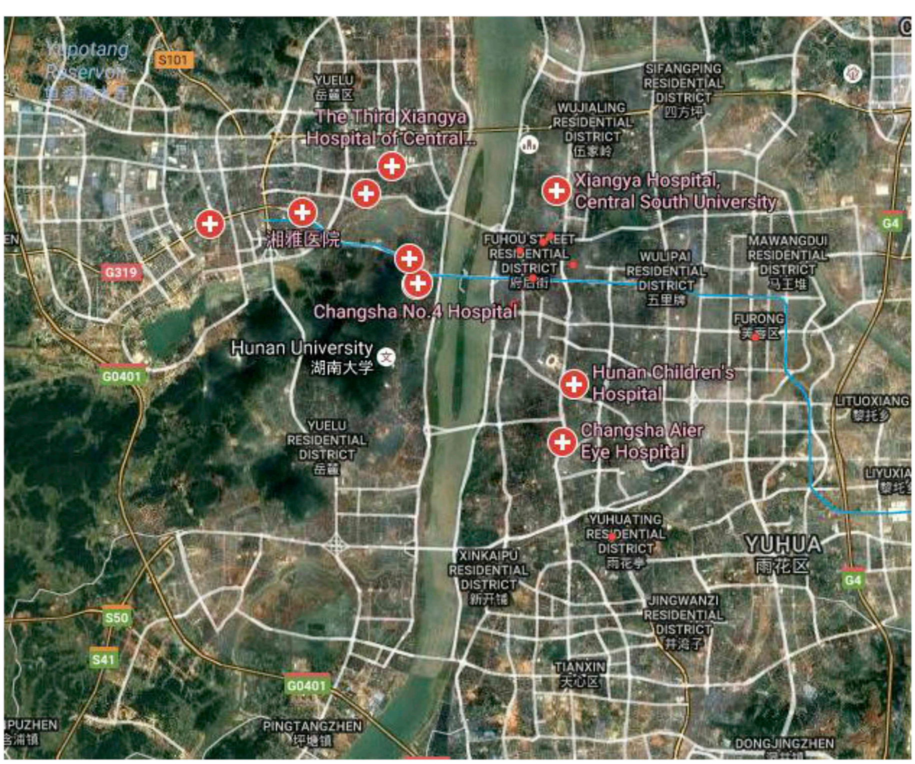

Fig. 4. Hospital geographical distribution map.

through the iterative mechanism to facilitate patients to choose good hospitals.

4. Data acquisition and analysis

The experimental data originated from the "Mobile Medical" project of the Ministry of Education–China Mobile joint laboratory conducted from May 2013 to December 2015.32,268,244 were treated with Central South University's cooperation with seven hospitals. The distribution of hospitals in the map is shown in Fig. 4.

The actual map area of 11,819 square kilometers covers the population of 375 million people. The treatment staff obtained 2987 evaluation data through the mobile APP data collection. A total of 2040 valid data were retained through screening.

This paper selected samples consistent with the demographic characteristics of the Chinese population (from the 2015 official statistics of the National Bureau of Statistics) to make the sample representative that conforms with the characteristics of Chinese people. The official demographics can only be studied by gender and age and cannot be collected based on the income, occupation, and other characteristics of distribution. Thus, only the gender, age, and disease type of the three characteristics of the contrast are given focus.

Table 1 lists the data sampling. The data shows that the number of personnel involved in the statistics should be consistent with the national gender and age distributions of personnel. The proportion of these personnel for the accurate calculation of the initial confidence of the user for the hospital is considerably beneficial.

This experiment adopts the national evaluation system for nine hospitals. From 2012 to 2015, the MOH assessed the top three hospitals in China based on the legal structure guarantee (L), technical structure assurance (T), and the quality of information distribution (Q). The data are shown in Table 2.

Table 1
List of data samples.

$\varphi[K]$	Option	Number of samples	Sample ratio/%	National population ratio/%
sex	male	1030	50.5	51.3
	female	1010	49.5	48.7
age	15–19	130	6.4	7.0
	20–29	860	42.2	17.3
	30–39	510	25.0	15.6
	40–49	270	13.2	14.2
	≥50	270	13.2	25.4
education	Below Bachelor	490	24.0	
	Bachelor	1320	64.8	
	Master	220	10.8	
	Doctor	10	0.5	
income	≤2000	480	23.5	
	2001–4000	1220	59.8	
	4001–7000	170	8.3	
	≥7000	170	8.3	
profession	Student	220	10.8	
	Civil servant	80	3.9	
	Institutions staff	490	24.0	
	Enterprise staff	370	18.1	
	Foreign workers	60	2.9	
	Private enterprise	300	14.7	
	staff	32	15.7	
	Freelancer other	20	9.8	
type of disease	hypertension	780	61.8	24.4
	High blood sugar	200	9.8	11.9
	High blood lipids	240	11.8	11.1
	diabetes	390	19.1	7.2
	Other chronic	360	17.6	12.1
	diseases no	750	36.8	

Table 2
MOH on hospital assessment indicators. The average score for 2040 valid data results is obtained through third-party feedback. The results are shown in Table 3.

	2012			2013			2014			2015		
Name	Q	T	L	Q	T	L	Q	T	L	Q	T	L
Xiang Ya hospital	91	94	88	93	97	91	92	95	89	94	92	90
2thXiangYahosiptal	96	99	96	97	92	95	94	99	91	95	96	93
3thXiangYahosiptal	84	90	79	88	91	88	80	89	80	89	92	79
Ai er Eye hospital	76	82	66	83	88	74	80	90	88	86	88	80
Children hospital	84	90	76	80	90	84	76	88	70	90	90	90
No.4 hospital	60	60	64	72	78	76	85	82	80	82	84	80
No.8 hospital	68	72	68	72	70	70	60	60	64	70	70	70

5. Results and discussion

Fig. 5 reflects the comparison of conclusions obtained through the confidence model over time in social networks. The initial confidence index of several well-known hospitals, such as Xiangya 1, 2, 3, and children's hospitals is high based on the statistics. These hospitals have a high national score and good medical technology. The confidence index of the three hospitals decreased with the advancement of the investigation time. Particularly, the third-party evaluation is low when the ranking of a country is high. The current index in each stage of the review decreases, which directly affects the next user choice and makes a short but significant $\widetilde{q_i^{n+1}}$drop. Two hospitals have the highest score from 97 down to 50, which fully illustrate that user selection has a strong influence. The lower score of the national hospital is due to good quality of service, short patient waiting time, and the comprehensive score in the APP display. Hospitals on the APP display dynamic changes to provide users the best recommendations, help patients choose the right hospital fora timely medical treatment, and reduce the wait for wards and doctors Table 3.

Fig. 6 reflects the number of people involved in evaluating the model and confidence in the conclusion. Fig. 6 shows the initial condition and the composite state ranking of the confidence index. As the number of participants increases, the time moves forward, and the current recommendation of all index changes of hospital confidence is obvious. When the number of participants is 800, the ranking of the Xiang Ya hospital has be changed, and the score changed from 73 to 93. The score indicates that, the number of participants is higher, and the quality of service of the hospital becomes more important when the sample data is larger. When the participants reach 2,000, the children's hospital scores are higher than other hospitals. The trend from the children's hospital changes point of view and has been in a steady rise, which indicates the quality service of the hospital and technical evaluation according to national authorities and third-party evaluation of the double recognition.

The study of the model must consider the various eigenvalues of the actual participants. These eigenvalues reflect the comprehensive evaluation of the specific population for each type of hospital. The distribution of the sample population is an important feature in social networks, which is in favor of APP in the recommending the next data that reflects objectivity.

Among various eigenvalues, we choose age, income, and education as research objects. The hospital inspects these three eigenvalues.

Fig. 7a reflects the age structure for the evaluation of the hospital. The figure shows that the sampling population of different ages for various hospital evaluation indexes is different. For those whose ages are 15–19 years, the value of the hospital for the evaluation of children is high and reaches 99. When the national evaluation of several hospitals, such as Xiangya 1 or 2, is high, the evaluation score is not significantly high, which indicates that the age of the staff for professional hospitals and hospitals with low selectivity is obvious. For those whose ages are from 40 to 49 and 50 and above, several hospitals in the

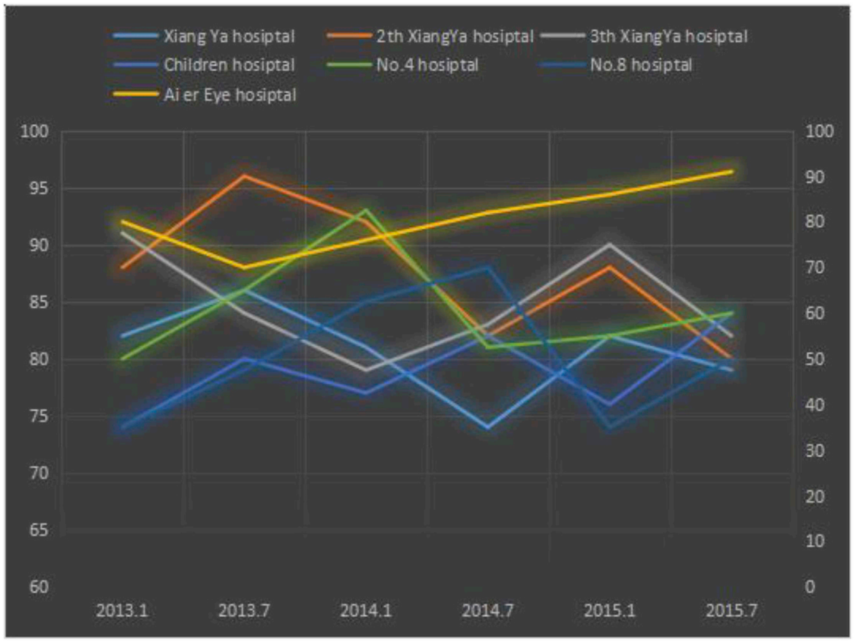

Fig. 5. Changes of hospital evaluation index over time.

Table 3
Results of third-party sampling.

Name	Reputation	Confidence
Xiang Ya hospital	72	55
2th XiangYa hospital	70	50
3th XiangYa hosipta	80	50
Ai er Eye hospital	89	70
Children hospital	99	60
No.4 hosipital	82	88
No.8 hosipital	80	90

country ranked high and are given high degree of trust. Their hospital evaluation is more inclined to include the overall technical level, medical prices, and follow-up protection of the hospitals.

Fig. 7b reflects the income structure of the population and hospital evaluation. Less than 2000 people are more willing to choose the treatment from the fourth to eighth hospital. Thus, the comprehensive score shows that the country ranks low, but the hospital receives a high score. Approximately 7000 people select the country with the most hospitals. The income of different people can be effectively separated through the APP evaluation mechanism, and suitable recommendations for different groups of people can be obtained.

Fig. 7c reflects the relationship between education and hospital evaluation. The figure shows that people who do not have bachelor's

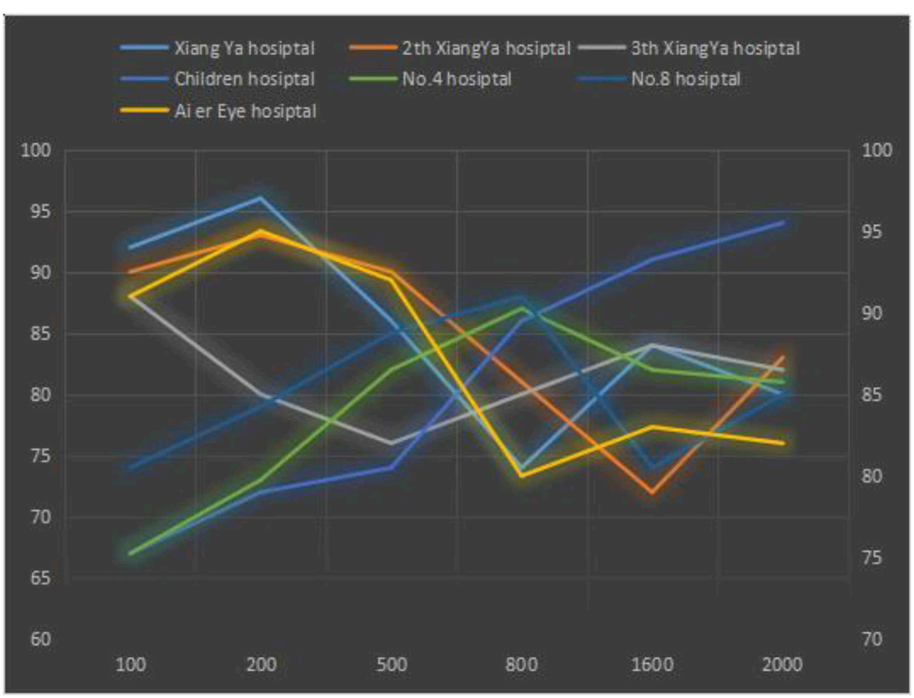

Fig. 6. Participants and hospital confidence index.

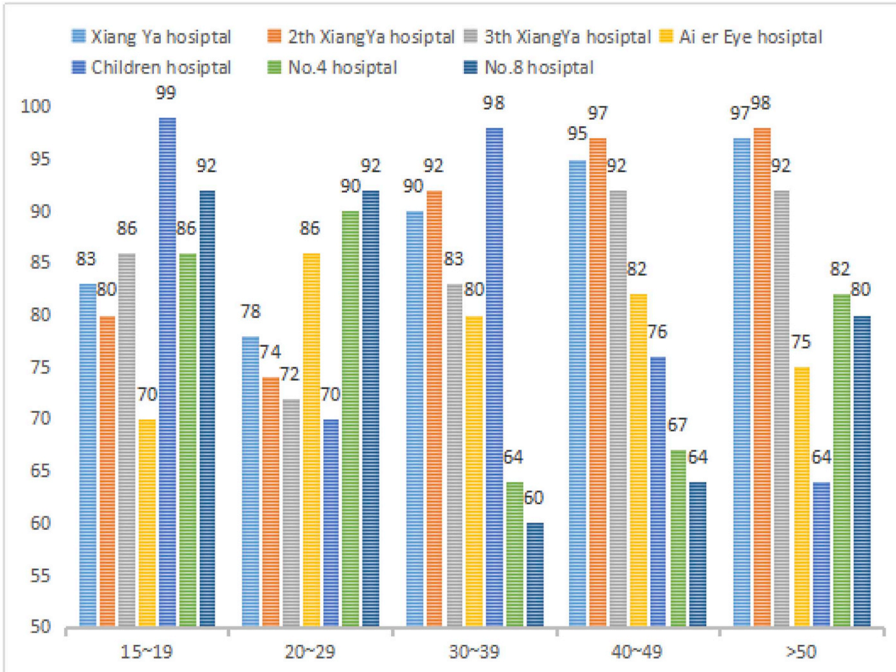

Fig. 7a. Age structure and hospital evaluation.

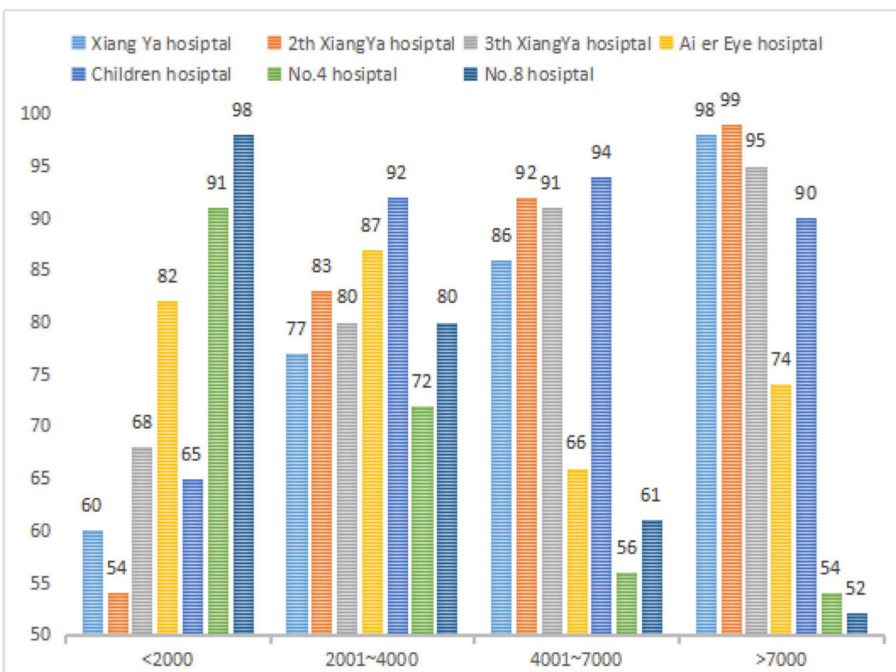

Fig. 7b. Income structure and hospital evaluation.

degrees have a high evaluation of hospitals with low national rankings, and those with master's degree are likely to choose hospitals with low rankings in the country, which indicate that people attach importance to the service quality of hospitals. Educated undergraduate and doctors tend to choose the country with better ranking hospitals, which indicates that they highly value the medical level of hospitals.

The different types of statistics and calculations show various types of personnel and time for the assessment mechanism of hospitals People in social networks can change real-time data, select the most suitable for their current data, and provide good recommendations for large cities. Large hospitals have a good staff diversion effect.

6. Conclusions

This paper establishes a model based on the evaluation index of hospital initial confidence and applies it to social networks by combining the national and third-party evaluations. Users can use the model through APP regardless of their region. A hospital analysis index query selects the best hospital for diagnosis and treatment. The model can locate different characteristics of the personnel by modifying the control variables. The establishment of a large data medical system provides good model characteristics.

In the future, the research of a large data medical system can be

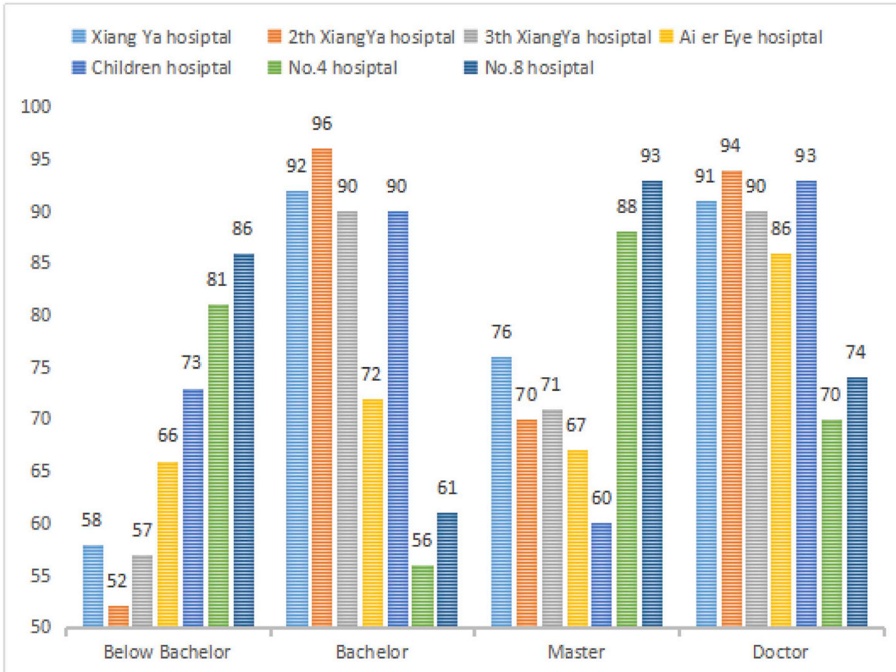

Fig. 7c. Education and hospital evaluation.

realized in the future by D2D real-time data acquisition and analysis to establish a more complete data set. Accurate data collection and effective information dissemination are realized in large data samples. Moreover, probability analysis and decision-making can be adapted. It is good for doctors to improve diagnostic test accuracy studies.

Supplementary Materials: All medical data management and system come from Central south university. If readers are interested in those data, you can visitor: http://www.xiangya.com.cn/english/

Funding

This work was supported in The National Natural Science Foundation of China(61672540); Hunan Provincial Natural Science Foundation of China (2018JJ3299, 2018JJ3682); China Postdoctoral Science Foundation funded project (2017M612586); Foundation of Central South University (185684); Major Program of National Natural Science Foundation of China (71633006)

Conflicts of interest

The authors declare no conflict of interest.

Acknowledgments

Not applicable.

References

[1] Y. Guan, B.J. Zheng, Y.Q. He, et al., Isolation and characterization of viruses related to the SARS coronavirus from animals in southern China, Science 302 (5643) (2003) 2029-2276-278.
[2] J. Zhang, X.J. Liang, Business ecosystem strategies of mobile network operators in the 3G era: the case of China Mobile, Telecommun. Pol. 35 (2) (2011) 1369–1372.
[3] W.U. Jia, Zhigang CHEN, Z.H.A.O. Ming, Effective information transmission based on socialization nodes in opportunistic networks, Comput. Network. 129 (24 December 2017) 297–305 Part 1.
[4] J. WU, Z.G. CHEN, M. ZHAO, Information Cache Management and Data Transmission Algorithm in Opportunistic Social Networks, Wireless Network (2018) 1–12, https://doi.org/10.1007/s11276-018-1691-6.
[5] W.U. Jia, Zhigang CHEN, Z.H.A.O. Ming, "SECM: status estimation and cache management algorithm in opportunistic networks", J. Supercomput. (–12) (2018) 1, https://doi.org/10.1007/s11227-018-2675-0.
[6] C.B. Huang, An Vehicle Network GPSR Routing Algorithm, Information Technology, 2017, pp. 1369–1372.
[7] B. XU, H. CAI, C. XIE, J. HU, Ubiquitous data accessing method in IoT-based information system for emergency medical services, IEEE Trans. on Industrial Inf. 10 (2) (2014) 1578–1586.
[8] H. Wang, Q. Zhang, J. Yuan, Semantically enhanced medical information retrieval system: a tensor factorization based approach, IEEE Access 5 (99) (2017) 7584–7593.
[9] D.G. Pfister, D.H. Johnson, C.G. Azzoli, American Society of Clinical Oncology treatment of unresectable non-small-cell lung cancer guideline: updated 2003, J. Clin. Oncol. 22 (2004) 330–353.
[10] Y. Tan, S.R. Montgomery, B.G. Aghdasi, H. Tian, H. Inoue, The effect of corticosteroid administration on soft tissue inflammation associated with rhBMP-2 use in a rodent model of inflammation, Spine (Phila Pa 1976 38 (10) (2012 May 1) 806–813.
[11] A. Agarwal, C. Baechle, R. Behara, X. Zhu, A natural language processing framework for assessing hospital readmissions for patients with COPD, IEEE J. Biomed. Health Inf. (99) (2017) 1-1.
[12] H. Greenspan, B.V. Ginneken, R.M. Summers, Guest editorial deep learning in medical imaging: overview and future promise of an exciting new technique, IEEE Trans. Med. Imaging 35 (5) (2016) 1153–1159.
[13] J. WU, Z.G. CHEN, "Sensor communication area and node extend routing algorithm in opportunistic networks", Peer-to-Peer Netw. Appl. 11 (1) (January 2018) 90–100, https://doi.org/10.1007/s12083-016-0526-4.
[14] C. Free, G. Phillips, L. Galli, et al., The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: a systematic review, PLoS Med. 10 (1) (2013) 145–149.
[15] Peiyuan GUAN, W.U. Jia, Effective data communication based on social community in social opportunistic networks, IEEE Access 7 (1) (2019) 12405–12414, https://doi.org/10.1109/ACCESS.2019.2893308.
[16] C. Doukas, T. Pliakas, I. Maglogiannis, Mobile Healthcare Information Management Utilizing Cloud Computing and Android OS 2010 (10) (2010) 1037–1040.
[17] W.U. Jia, Zhigang CHEN, Z.H.A.O. Ming, "Weight distribution and community reconstitution based on communities communications in social opportunistic networks", Peer-to-Peer Netw. Appl. 12 (1) (January 2019) 158–166, https://doi.org/10.1007/s12083-018-0649-x.
[18] Y. Ren, R.W.N. Pazzi, A. Boukerche, Monitoring patients via a secure and mobile healthcare system, IEEE Wireless Communications 17 (1) (2010) 59–65.
[19] A. Atreja, S. Khan, J.D. Rogers, et al., Impact of the mobile HealthPROMISE platform on the quality of care and quality of life in patients with inflammatory bowel disease: study protocol of a pragmatic randomized controlled trial, JMIR Res. Protoc. 4 (1) (2015).
[20] W.U. Jia, YANlin TAN, Zhigang CHEN, Z.H.A.O. Ming, "Decision based on big data research for non-small cell lung cancer in medical artificial system in developing country", Comput. Methods Progr. Biomed. 159C (2018) 87–101, https://doi.org/10.1016/j.cmpb.2018.03.004.
[21] M. Rahimi-Gorji, T.B. Gorji, M. Gorji-Bandpy, Details of regional particle deposition and airflow structures in a realistic model of human tracheobronchial airways: two-phase flow simulation, Comput. Biol. Med. 74 (2016) 1–17.

[22] A. Alicante, A. Corazza, F. Isgrò, et al., Unsupervised entity and relation extraction from clinical records in Italian, Comput. Biol. Med. 72 (C) (2016) S001048251630004X.
[23] J. Luo, Z. Feng, J. Zhang, et al., Dynamic frequency feature selection based approach for classification of motor imageries, Comput. Biol. Med. 75 (C) (2016) S0010482516300580.
[24] E.E. Küçük, K. Yapar, D. Küçük, et al., Ontology-based automatic identification of public health-related Turkish tweets, Comput. Biol. Med. 83 (2017) 1–9.
[25] A. Gandhamal, S. Talbar, S. Gajre, et al., Local gray level S-curve transformation - a generalized contrast enhancement technique for medical images, Comput. Biol. Med. 83 (2017) 120–133.