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Article

Ontology-Supported Double-Level Model Construction for International Disaster Medical Relief Resource Forecasting

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Abstract: In a disaster, mass casualties lead to a surge in demand for medical services. Some relief actions have been criticized for being ill-adapted to dominating medical needs. This research established a disaster medical relief planning model in 3 steps. 1. Establishing the two-level conceptual model. 2. Using the ontology method to describe the hierarchy and relating rules of the terms and concepts associated with the model. 3. Using an ontology-support case-based reasoning approach to build the case similarity matching process, which can provide a more efficient system for decision support. A case study validated the model and demonstrated its usage.

Keywords: Disaster medical relief; planning; ontology-supported; double model

1 Introduction

In the past few years, many disasters have affected people all over the world. In the event of such disasters, mass casualties would lead to a surge in demand for emergency medical services. In some countries, especially low and middle income countries, international actions are needed [1].

International action is based on the preparation of medical resources, such as staffing, necessary equipment, and required medical supplies [2]. Medical resource preparation is based on determining the likely number of injury or patient during the action [3]. “Scenario-Response” model is the main method for emergency management study. This model has been applied in making Readiness Strategic Plan, simulating exercising, predicting, early warning and so on [4]. Some of the medical relief “Scenario-Response” models focus on establishing the disaster scenario which could determine the likely amount and composition of injury or patient stream after disaster outburst [5]. Other scenario models are optimization models which focus on optimizing the medical evacuation decision making, priority for receiving care, the medical resource effective allocating, etc. [6,7]. All these models tend to focus on providing life-saving trauma care in the early disaster relief period.

However, in recent years, foreign medical teams deployed to disasters relief have been found to have arrived too late to provide life-saving trauma care. Also, they have been criticized for focusing too much on trauma care and not adapting to controlling health needs in affected regions [8]. In the disasters, local health services may be ruined and require international help, not only in dealing with the injuries rescue but also maintaining routine health service for local people [9,10]. Some articles focus on the children and maternal in some armed conflicting region [11]. They are more vulnerable and easy to be injured when facing the disaster [12]. When lacking the local professional service for them, humanize crisis is more likely to occur. Some other articles also reported that people with chronic diseases (PCDs) are easy to get hurt in the disaster [13,14].

So when we consider establishing the Scenario model for international medical relief, we should not only take emergent medical rescue needs into consider, but also the normal local health service coverage and population health condition.

2 Research Background and Research Steps

So far, there has been no research on establishing models that take into account not only the disaster characteristics but also local medical service status and local residents' basic health condition.

The main concern of World Health Organization (WHO) is whether there would be a pandemic after the disaster. WHO also published a general guideline for international medical rescue teams. But according to some research, this guideline was not fully followed due to several reasons. One reason is that this guideline is not associated with the local reality [15].

On this basis, we established a dual level scene-based forecasting model framework for the international disaster medical relief mission.

For the application of this scenario model, the key basis is to construct the knowledge base of actual case expression. As disaster medical relief is complicated and multi-disciplined, there are many concepts, terminology and relationship rules. Ontology technology solves the problems of knowledge expression, sharing and reuse [16]. Therefore, we use ontology method to construct the knowledge base of the model. This knowledge base can support the scene-based forecasting model and has the ability of decision support [17].

To support disaster medical relief decisions, the model should have the ability to learn from historical cases and to generate medical requirements for new case based on past requirements in historical cases. Case-Based Reasoning (CBR) is an effective problem solution in Artificial Intelligence (AI). It could retrieve historical cases based on certain features and find solutions or decision recommendations based on historical cases. Therefore, it could provide a more convenient retrieval process to provide medical planning recommendations based on knowledge of past disaster events. Furthermore, the structure and query capabilities of the ontology support this approach well. Relevant studies show that ontology facilitates similarity assessment by linking query terms with case-based terms [18]. Thus, an ontology-supported case-based reasoning (OS-CBR) approach could be developed for the international medical rescue resource forecasting model.

On this basis, this paper develops an ontology-supported dual resource forecasting model in 3 steps. First, a two level conceptual model (the disaster scene level and the country scene level) is established. Second, ontology method is used to express the common knowledge involved in the model by using Protege software, and query rules and ontology inference device are established with Jena. Third, an ontology-support case-based reasoning (OS-CBR) approach is established which enables the model to learn from historical cases and develops medical resource preparation plans for new case.

3 The Conceptual Dual Scene-Based Forecasting Model Construction

3.1 Overview of the Conceptual Dual Scene-Based Forecasting Model

The model consists of two different levels of scenarios: a disaster scenario, in which mortality rate, the number of the wounded, the injury structure are influenced by the types of disaster and the damage degree; a country scenario, in which the health requirements are influenced by the local health condition, medical service accessibility, the infectious disease incidence and the professional services provided to the special people such as maternal and child.

The outcome of this model is the medical service requirements which are the basis of medical relief planning. The model could provide the likely number and structure of injury or patients based on which the composition of staffing, requisite equipment, medicine and other needed supplies could be forecasted.

The abridged general view of the model is shown in Fig. 1. The disaster-scenario level model is related to the disaster type, degree, disaster area and time. This model could have a great impact on the medical requirements in the first period (T1) when most survivors are found [19].

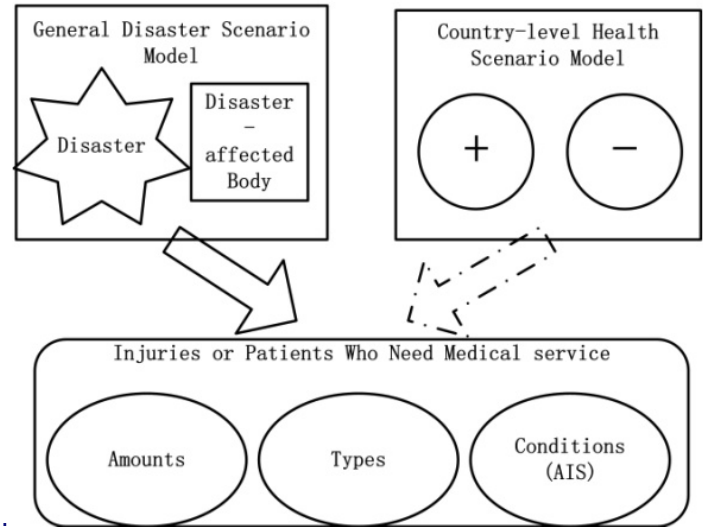

Figure 1: Abridged general view of the dual-level scene-based forecasting model

But with the expansion of time, especially close to the end of golden rescue time, the country-level model increasingly influents the medical needs in the second period of disaster relief time (T2) [20]. The country-level model is related to the characteristic factors of the country's health condition and medical service accessibility.

3.2 Level 1–Disaster Level Scene-Based Forecasting Model

There are lots of researches on the models of emergent medical service requirements forecasting. Reviewing these researches, the indexes to describe the emergent medical service requirements have high correlation with disaster characteristic such as the time, area, type, damage degree and fragility of disaster-affected body [21,22]. If the affected region has high fragility such as poor building quality, the amount of injury and severe injuries will also increase [23].

Based on these researches, a conceptual model of disaster scene level is established. Injury Amount (IA), Consist of Injury Condition (CIC) and Consist of Injury Type (CIT) are used as outcome indexes to describe the medical service requirements. Disaster Type (DTy), Disaster-affected-body Fragility (DF), Disaster-affected Population (DP), Disaster Degree (DD), and Disaster Time (DTi) are used as income indexes. The general view of the disaster scene level model is shown in Fig. 2.

The mathematical expression of the model is as follows:

$$\{IA, CIC, CIT\}\text{-}f\{DTy, DC, DP, DD, DTi\} \quad (1)$$

This expression could be decomposed into 3 sub-expressions.

$$IA = f'(DP, DD, DF, DTi) \text{ (when } DTi \leqq 7\text{, value DTi the actual day number; when } DTi > 7\text{, value } DTi = 7) \quad (2)$$

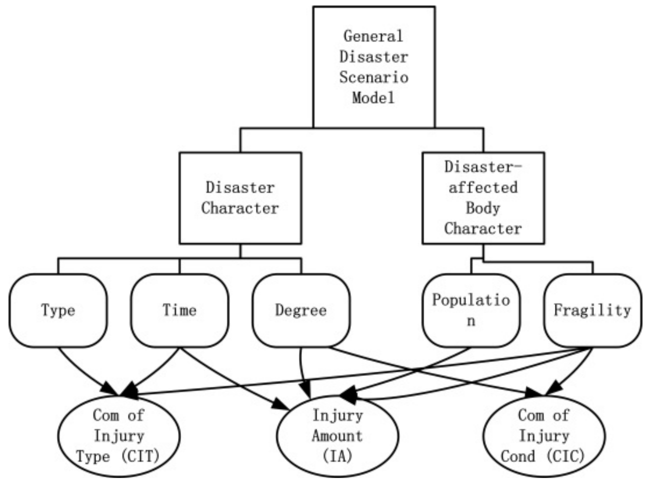

Figure 2: General view of the disaster scene level model

In the sub-expression, DP is the basic number of injury amount which has positive correlation with DD and DF. According to earthquake medical relief researches, the injury amount would increase rapidly during the T1 period which often lasts from the 1st day until 3rd or 7th day after earthquake. Then, at the end of the T1 period, the injury amount would increase slightly. So in the expression, actual number of the day would be used when DTi $\leqq$ 7 and 7 is used as day number when DTi > 7.

$$CIC = f''(DD, DF) \tag{3}$$

In this sub-expression, the relationship of CIC and DD, DF and CIC is expressed. CIC indicates consisting of critical injury, severe injury and light injury. The classification of injury condition is based on the Abbreviated Injury Scale (AIS) which is commonly used in emergency triage. When the DD and DF are higher, consisting of critical injury and severe injury would be higher, vice versa.

$$CIT = f'''(DTy, DD, DF) \tag{4}$$

The relationship between CIT and DTy, DD, DF is expressed in this sub-expression. Injury type in the disaster is determined by the DP while the injury structure is determined by DD and DF.

3.3 Level 2–Country Level Scene-Based Forecasting Model

With the expansion of time after T1 period, the number of injuries gradually increases steadily, while the number of patients caused by poor coverage of health service, poor sanitary condition, poor immunization and other local health problems gradually increase rapidly [24]. This change could be described in two dimensions. One is the new occurrence of patients, the other is the injury amount change.

If the local residents' health, medical service coverage and infectious disease control are in good condition, the amount of injuries could be decreased especially the critical or severe injuries. Children, maternal and people with chronic diseases would be taken good care of. Preventable infectious diseases would not outbreak and the health of local residents would in a controllable level.

If the local situation is in a bad way, severe injuries could turn to critical injuries and critical injuries could lose their life. The local people especially children, maternal and the elders could suffer huge humanitarian crisis while infectious diseases could become pandemic.

The country level scene-based forecasting model is based on over 1,000 health related indexes monitored by WHO in 194 countries. 6 types of these indexes are selected to reflect the influence.

There are mainly two types of outcome indexes. One type reflects the treatment of injury, such as Adjusted Injury Amount (A-IA) and Adjusted Consist of Injury Condition (A-CIC). Another type reflects disease treatment or control during period T2, such as Patient Amount (PA), Disease Consist (DC) and Infectious Disease Prevalence (IDP).

The input index of this model includes two types. One type reflects the resilience of local medical service. Another reflects the fragility of the local population health condition. The first type of index is called positive index with "+" mark. The second aspect of index is marked with "-" because it has negative effects.

The positive index includes 3 kinds of indicators which are Health Coverage (HC), Professional Service for Special Population (PSSP) and Infectious Disease Control (IDC). The negative index includes 3 kinds of indicators which are General Health (GH), Special Population Health (SPH) and Infectious Disease Consist (IDC).

The general view of the country level model is shown in Fig. 3.

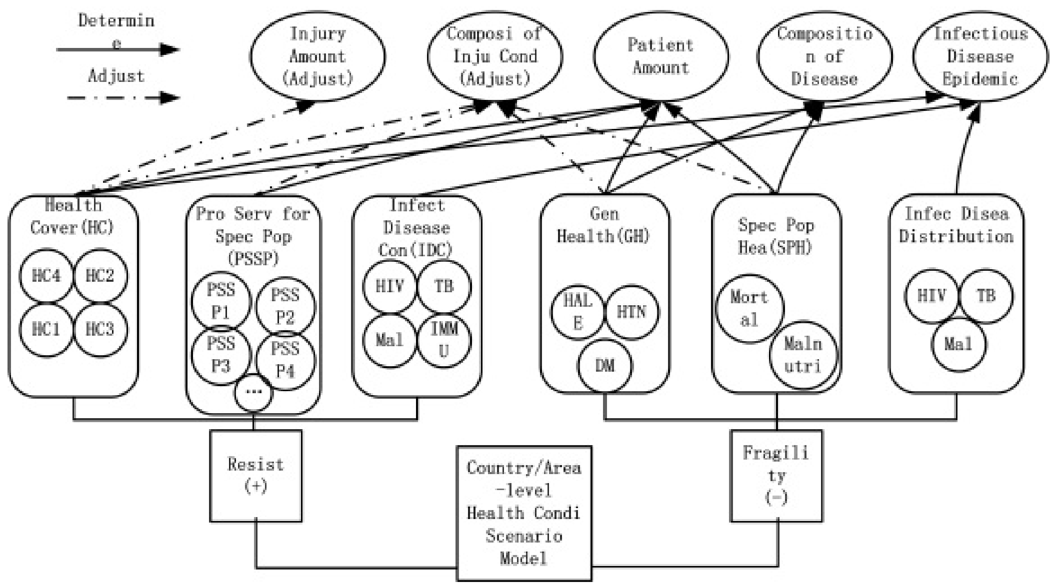

Figure 3: General view of the country level model

In the figure, Health Coverage (HC) index includes 4 kinds of indicators. HC1 means the basic hospital access indicated by hospital beds per 10,000 populations. HC2 means the medical-staff density indicated by physician density per 1,000 populations. HC3 means the access to essential medicines indicated by median availability of selected generic medicines. HC4 means the compliance with international regulation indicated by the country's international health regulation core capacity. Professional Service to Special Population (PSSP) index includes 3 kinds of indicators. PSSP1 means family planning indicated by the percentage of married women of reproductive age who satisfied with modern methods. PSSP2 means antenatal delivery and care condition indicated by the percentage of antenatal care coverage. PSSP3 means health-seeking behavior for child indicated by the percentage of children with suspected pneumonia taken to an appropriate health provider. Infectious Disease Control (IDC) index includes 4 kinds of indicators. HIV means HIV therapy condition indicated by estimated antiretroviral therapy coverage among people living with HIV. TB means tuberculosis therapy indicated by tuberculosis treatment coverage for all forms of tuberculosis. SH means Sanitation and hygiene indicated by the percentage of population using basic sanitation services. IMMU means the immunization coverage indicated by DTP3 immunization coverage among 1-yearolds.

General Health Condition (GHC) index includes 3 kinds of indicators. HALE means health adjusted life expectancy indicated by the adjusted life expectancy weighted for the level of health-related quality of life. HTN means the prevalence of raised blood pressure indicated by the percent of defined population with raised blood pressure (SBP $\geq$ 140 or DBP $\geq$ 90). DM means the prevalence of raised blood glucose. Special Population Health (SPH) index includes 2 kinds of indicators. Mortality means the maternal mortality ratio (by 100,000 live birth) and under-five mortality indicated by the probability of dying by 5 per 1000 live birth. Malnutrition means the prevalence of stunting among children under 5 years old. Infectious Disease Distribution (IDD) index includes 3 kinds of indicators. HIV prevalence is indicated by the estimated number of people (all ages) living with HIV. TB means the tuberculosis prevalence indicated by number of new cases per 100,000 population. Malaria prevalence is indicated by number of new cases per 1000 population at risk.

The mathematical expression of the model is as follow.

$$\{A\text{-}IA, A\text{-}CIC, PA, CD, IDE\} - g\{HC, PSSP, IDC, GHC, SPH, IDD\} \quad (5)$$

This mathematical expression could be decomposed into 5 sub-expressions.

$$A\text{-}IA = -g'(HC, PSSP)$$

$$A\text{-}CIC = -g''(HC, PSSP) + g''(GH) \quad (6)$$

$-g'$ and $-g''$ indicate negative correlation. When HC, PSSP is high which means local health service is in good condition, A-IA and A-CIC are low which mean the injury amount and the ratio of critical or severe injuries decrease. g'' indicates positive correlation. When GH is high, A-CIC is high indicating critical or severe injuries increase.

$$PA = P*[g'''(GHC)-g'''(HC)] + SP*[g'''(SPH)-g'''(SPS)] \quad (7)$$

$$DD = -g''''(HC, PSSP) + g''''(GHC, SPH) \quad (8)$$

P indicates the total population affected by the disaster. SP indicates the special population including children, women and the elderly. g''' and g'''' indicates positive correlation while $-g'''$ and $-g''''$ indicates negative correlation. So these two expressions means the higher value the GHC and SPH is, the larger amount of patients and severe diseases would occur. Vice versa.

$$IDE = -g'''''(IDC, HC) + g'''''(IDD) \quad (9)$$

This sub expression means if the IDC and HC is in good condition, the possibility of IDE is low. If IDC is in poor situation, the possibility of new infectious disease pandemic is high.

4 Ontology Based Knowledge Base Construction

4.1 Framework Description of Constructing the Ontology-Support Model Knowledge Base

The overall research steps of constructing the ontology-support model knowledge base are as follows. First, by collecting historical disaster medical relief cases, common knowledge is extracted based on the feature indicators of various disasters, local residents' health condition and medical service coverage. Secondly, the common knowledge involved in the conceptual model is structured. Then, an ontology approach is used to describe the hierarchy of related concepts and terms and their association rules. Three kinds of ontology are established as the foundation of the knowledge base for the model. Thirdly, similarity inference, numerical query and other inference and query rules are established, and ontology inference device is built by Jena. Finally, the dual scene-based forecasting model is applied (Fig. 4).

4.2 Knowledge Acquisition

The sources of the knowledge acquisition are: (1) Published literature, books and regulations of disaster relief mission; (2) Published literature and books on historical cases; (3) The Sustainable Development Goals (SDG) of WHO in 2030; (4)Literature on summarizing the experience of international disaster medical relief missions.

4.3 Knowledge Semantic Extraction

Knowledge semantics are extracted using the meta-ontology approach. "Class" express concepts; "Properties" express attributes and relationships; "Rules" express decision algorithms (Fig. 5).

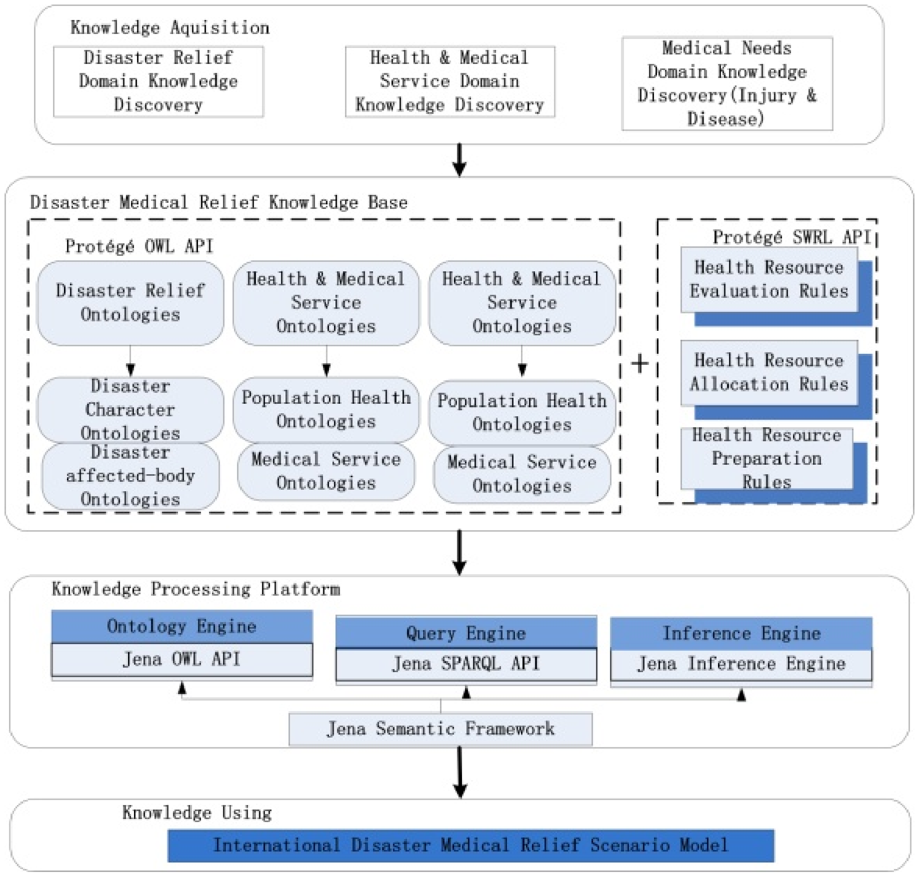

Figure 4: Framework of constructing the ontology-support knowledge base for the model

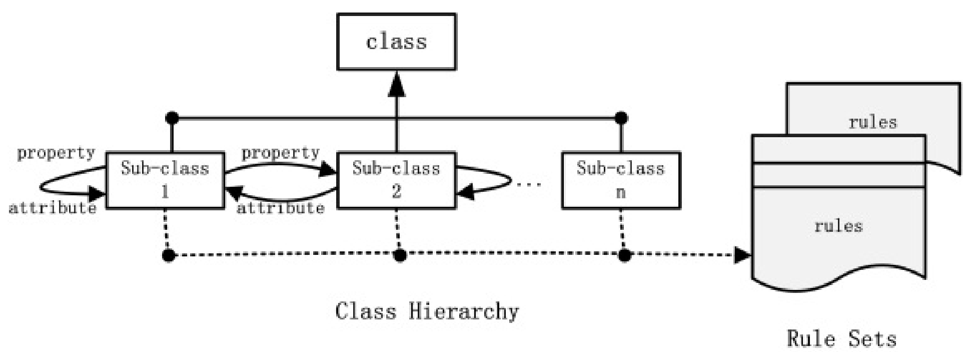

Figure 5: The meta-ontology approach used in knowledge semantic extraction

4.4 Knowledge Representation

4.4.1 Class

Four sub-classes are set under the root class "Thing". They are respectively named as "Country", "Disaster_Condition_Index", "Health_Condition_Index" and "Medical_Needs_Condition".,Class hiberarchy is used to create detailed knowledge system for each sub-class. (Fig. 6)

The class "Country" describes the nation or area where international medical relief is needed. Based on the scene-based forecasting model, the Class-Property framework is established, which includes indexes of disaster condition and health condition associated with the medical relief.

The class "Disaster_Condition_Index" consists of "Disaster_Character" and "Hazards_ Carriers_Character".

4.4.2 Property

The property "determineMedicalNeeds" describes the indicators which are related to medical requirement calculation at a high level.

The property "effectMedicalNeeds" describes the indicators which are related to medical requirement at a low level.

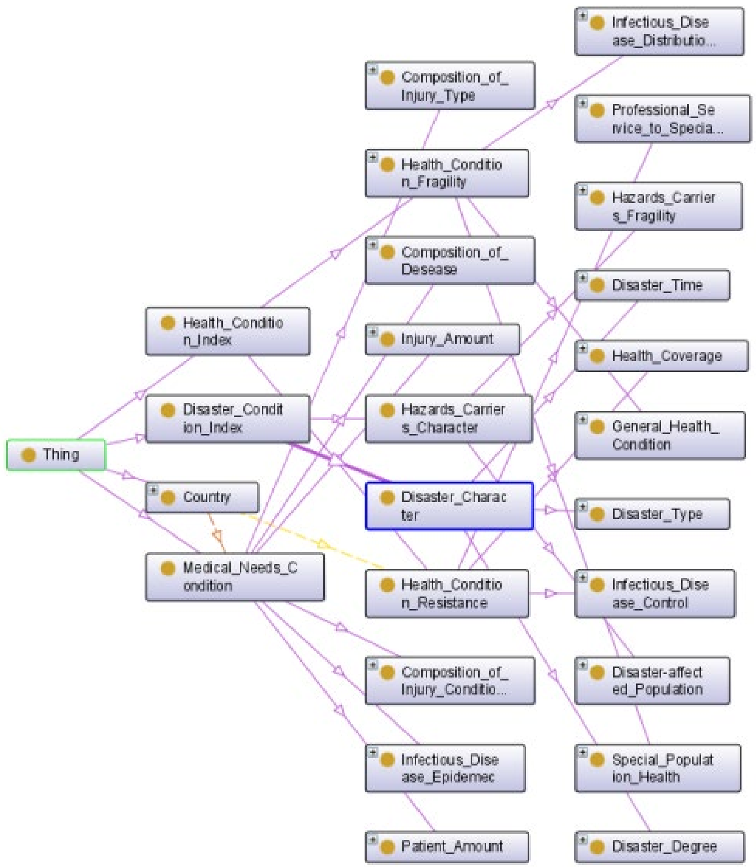

Figure 6: Framework of the classes

The property of "hasHealthConditionIndex" connects class "country" and indicators.

The property of "hasMedicalNeeds" connects the class "country" and medical requirement.

4.5 Rule of Inference and Inquire

Jena and SOEARQL are applied to complete the function of inference and query.

5 Development of the OS-CBR Approach

5.1 Overview of OS-CBR Approach

Historical cases of international medical relief could be stored and structured based on the ontology-supported knowledge base. Fig. 7 shows the over view of using the OS-CBR approach in disaster situation inference. If the similarity between the retrieved case and the new case is less than predefined threshold, adaptation case replaces reuse case.

5.2 Case Retrieval Phase

Case retrieval is the most important process in OS-CBR approach. When new international disaster medical rescue is needed, the OS-CBR system retrieves historical cases that are similar to the new one from a case base (CB). For example, for a new case C_n = {Armed Conflicts, Local, Syrian Arab Republic, Religion Conflicts ⋯} historical cases with similar secen features to C_n can be found through case retrieval.

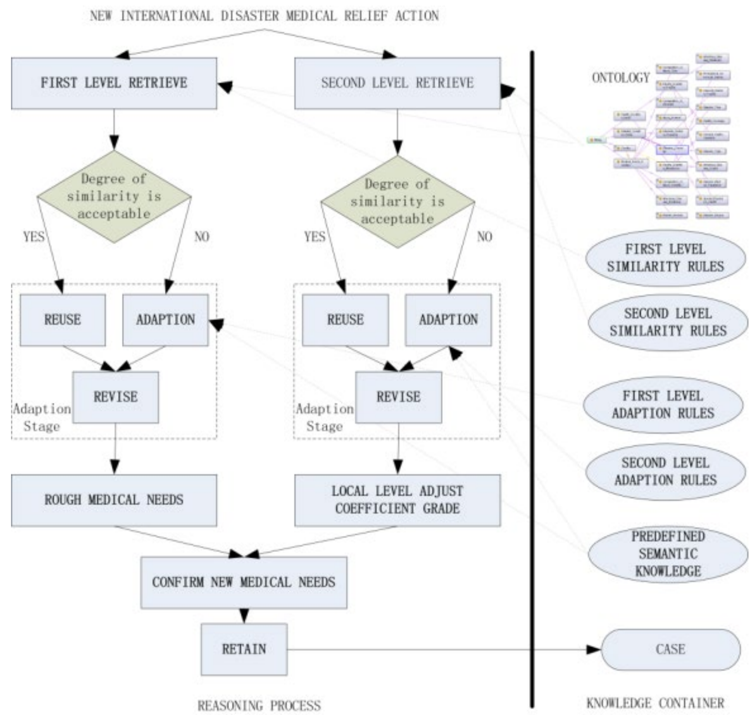

Figure 7: Overview of OS-CBR approach

According to the dual scene-based forecasting model, the case retrieval should be done twice. One is on disaster level and another is on country level.

5.2.1 Disaster Level Case Retrieval

The indexes of disaster level are mainly composed of feature indexes of the disaster and disaster affected body. The possible data types in the case retrieval of this level could be numerical and text string.

For the numerical data type, the similarity value is calculated by: (10 indicators assumed)

$$S_{ij} = \left(1 - \sqrt{\left(\frac{C_{ij} - X_i}{\max(C_i) - \min(C_i)}\right)^2}\right) \times \frac{W_i}{10} \tag{11}$$

S_{ij} stands for the similarity of indicator "i" in the new case, compared to the same indicator in the historical case j. C_{ij} is the value of the indicator i in the historical case j, X_i is the value of i in new case, W_i is the weight of indicator i, and $\max(C_i)$–$\min(C_i)$ is the largest scope of the value of C_i in historical case j.

5.2.2 Country Level Case Retrieval

Most of the country level's feature indicator data type is numerical but in different units. In order to deal with this, Standardized Euclidean Distance (SED) is chosen to calculate the similarity.

First, all the numerical data is standardized to mean or standard deviation:

$$X_i^* = \frac{X_i - m_i}{s_i}, C_{ij}^* = \frac{C_{ij} - m_i}{s_i} \tag{12}$$

X_i is the input value of the indicator i, X_i^* is the standardized value of X_i, m_i is the mean value and s_i is the standard deviation.

Then, when certain feature indicator's similarity is calculated, the SED is obtained by the following rule:

$$d_{kj} = \sqrt{\sum_{i=1}^{n}\left(\frac{X_i - C_{ij}}{s_i}\right)^2} \quad (k=1,2,3) \tag{13}$$

"dkj" is the SED of a set of indicators in type k in the new case, compared to the same indicators of a historical case. "n" is the total number of indicators in type k. Xi is the input value of indicator i, Cij is the value of indicator i in case j.

SED's value is between 0 (most different) and 1 (most similar). For example, when comparing indicators of type 1 in the new case, C1 is more similar to the new case than C2, if the d11 is shorter than d12.

The process of case retrieval is as follow: When a new case is input into the system, the case base which has stored all the historical data of WHO's SDG of 2030 is searched to retrieve cases with a similar feature type by type. The similarity between the new case and the stored cases is determined by calculating the SED of the feature indicators. Once the most similar cases of different types of indicators have been obtained, they will be used in the case adaptation phase.

5.3 Case Adaption Phase

The substitution strategy is used for case adaptation phase in this research. Substitution is used when parts of the medical requirements in the retrieved historical case are in conflict with the new case. Predefined ontology semantic knowledge base is used to perform Substitution. The process of substitution case adaptation is as follow: First, the distance between every chosen historical case's medical requirements in the retrieval phase and the new case's medical requirements are calculated. If the differences of the recommended requirements and those of the chosen ones are acceptable, then the requirements are considered as valid ones.

5.4 Case revision and preservation

After case retrieval and case adaption, the recommended medical requirements are revised for suitability by experts. The revised results are retained temporarily in the database. After the mission, the results are compared to the actual scene features and medical requirements. They are retained in the case base for future use.

6 Model Application Results and Discussion

As an example, the model is used to analyze the medical relief requirements in Syrian Arab Republic, where armed conflicts had broken out in 2011.

First, the disaster level scene feature indicators are obtained and ontology-supported knowledge base is used to establish the instant of the disaster level scenario. The indicators include disaster type (armed conflict), damage degree (severe), cause of disaster (Arab Spring), duration of the disaster (more than 2 years), affected area (whole country) and affected population (25,235,000). Then, the OS-CBR approach is used to find the most similar historical case. The caculated similarity results are shown in Tab. 1.

As showed in Tab. 1, the most similar case is Case 1, the armed conflicts happened in Yemen. If the result of disaster level model is the only consideration, similar medical resource plan should be taken. As the model has two levels, the country level feature indicators are obtained both in Syria and Yemen and ontology-supported knowledge base is used to establish the instants of both countries' local level scenario. The values of indicators in both countries are showed in Tab. 2.

Table 1: Feature indicator Similarity results from disaster level using OS-CBR approach

Feature indicator	Similarity							
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	
Disaster type	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Damage Degree	1.00	1.00	1.00	1.00	0.50	0.75	0.50	0.50
Cause of disaster	1.00	1.00	0.87	0.73	0.37	0.52	0.34	0.28
Duration of disaster	1.00	1.00	0.45	0.83	0.83	0.72	1.00	0.63
Degree	1.00	1.00	1.00	1.00	0.50	0.75	0.50	0.50
Affected area	1.00	1.00	1.00	1.00	0.50	0.50	0.50	0.50
Affected population	0.92	0.89	0.92	0.48	0.73	0.63	0.28	0.49
Hit area	1.00	1.00	1.00	1.00	0.50	0.50	0.50	0.50
Start time	1.00	1.00	0.45	0.83	0.83	0.72	1.00	0.63
Location	0.97	0.92	0.89	0.27	0.72	0.48	0.36	0.50
Total	0.99	0.97	0.88	0.76	0.66	0.66	0.57	0.56

Table 2: The value of indicators for country level model in Yemen and Syrian Arab Republic

Type	Indicator	Yemen	Syrian Arab Republic
Health Coverage	HC1	7	15
	HC2	0.311	1.546
	HC3	46	63
	HC4	3.93/60	4.8/93
Professional Service to Special Population	PSSP1	69.6	87.5
	PSSP2	49.1	91.1
	PSSP3	34	76.8
Infectious Disease Control	HIV	No data	18
	TB	59	80
	IMMU	DTP3:84	DTP3:70
General Health Condition	HALE	54	63
	HTN	30.7	24.5
	DM	11.3	14.6
Special Population Health	Mortality	385;47	68;17.4
Infectious Disease Distribution	HIV	No data	9,900
	TB	48	21
	Malaria	22.2	0

Data source: WHO's the Global Health Observatory theme pages (http://www.who.int/gho/en/).

The SED of each feature indicator of the country level model is calculated using OS-CBR approach. The results are showed in Tab. 3. From the results we could come to the conclusion that although Yemen is the most similar case to Syrian on disaster level, its SED of indicators on the country level is longer than global average to Syrian which means Syrian's situation on country level is quite different from Yemen. When concerning the health condition and service coverage, Syrian is more similar to Iran. When concerning the special population health condition and professional service offering, Syrian is more similar to Jamaica. When concerning disease control and infectious disease distribution, Syrian is more similar to Egypt. So the medical resource plan should adjust according to this result which means pay more attention to local service system recovery and supporting polio vaccination rather than more emergent medical resources delivery and lifesaving medical services in Yemen's resource plan. According to the WHO's response plan for these two countries, we could see that the main points in Yemen's plan are different from Syrian. So the recommendation of the dual level scene-based forecasting model fit the reality.

Table 3: SED results for second level model

Feature	Index	Indicator	Syrian	Yemen	SED (Yemen)	Outcome Case	SED (Outcome)	Global Average	SED (Global)
Type1	HC	HC1	15	7	0.7836	17	0.2385 (Iran)	19	0.4192
		HC2	1.546	0.311		1.49		2.9	
		HC3	63	46		66		60	
		HC4	4.8	3.93		9.4		9.1	
	GHC	HALE	63	54		61		59	
		HTN	24.5	30.7		25		27.5	
		DM	14.6	11.3		12.1		9.5	
Type 2	PSSP	PSSP1	87.5	69.6	0.8134	85	0.3157 (Jamaica)	76	0.6935
		PSSP2	91.1	49.1		87		75	
		PSSP3	76.8	34		75		60	
	SPH	Mortality	68;17.4	385;47		93;23		216; 40.8	
Type 3	IDC	HIV	18	No data	0.8392	27	0.4213 (Egypt)	50	0.5192
		TB	80	59		80		75	
		IMMU	DTP3:70	DTP3:84		DTP3:79		DTP3:85	
		SH	93	60		93		88	
	IDD	HIV	9,900	No data		1913		190,155	
		TB	21	48		15		142	
		Malaria	0	22.2		0		94	

7 Conclusion and Next Research Plan

In international disaster relief missions, people should take into account both disaster scenario and local medical and health scenarios when forecasting possible medical requirements. As a result, more realistic medical resource preparation plans can be developed. The aim of this research is to establish a dual scene-based forecasting model for international disaster medical relief.

More research is needed in the future. For example, the model indicators' type and weight should be dynamic over time, over areas and over events. What is more, the correlation between the input indicators and outcome indicators should be clearer and more calculable. Sensitivity and effectiveness analysis of the model is also required. The model should be examined by more international disaster medical relief mission practice.

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References

[1] C. M. Andrew and A. Bonnie, "Chronic diseases and natural hazards: Impact of disasters on diabetic, renal, and cardiac," *Prehospital and Disaster Medicine*, vol. 23, no. 2, pp. 185–194, 2008.

[2] G. S. Debarati, "Rapid assessment of health needs in mass emergencies: Review of current concepts and methods," *Wid Health Statist, Quare*, vol. 44, pp. 171–181, 1991.

[3] E. Y. Y. Chan and E. Sondorp, "Medical interventions following natural disasters: Missing out on chronic medical needs," *Asia-Pacific Journal of Public Health*, vol. 19, Special Issue, pp. 45–51, 2007.

[4] K. Mohan and M. Aramudhan, “Broker based trust architecture for federated healthcare cloud system,” *Intelligent Automation & Soft Computing*, vol. 23, no.3, pp. 477–483, 2017.

[5] P. P. Repoussis, D. C. Paraskevopoulos, A. Vazacopoulos and N. Hupert, “Optimizing emergency preparedness and resource utilization in mass-casualty incidents,” *European Journal of Operational Research*, vol. 255, no. 2, pp. 531–544, 2016.

[6] M. Fereiduni and K. Shahanaghi, “A robust optimization model for distribution and evacuation in the disaster response phase,” *Journal of Industrial Engineering International*, vol. 13, no. 1, pp. 117–141, 2017.

[7] W. Xu, Y. Ma and X. Zhao, “A Comparison of scenario-based hybrid bilevel and multi-objective location-allocation models for earthquake emergency shelters: A case study in the Central Area of Peking, China,” *International Journal of Geographical Information Science*, vol. 32, no. 2, pp. 236–256, 2017.

[8] J. D. Reinhardt, J. Li, J. Gosney, F. A. Rathore *et al.,* “Disability and health-related rehabilitation in international disaster relief,” *Global Health Action*, no. 4, pp. 7191–7197, 2011.

[9] L. Jennifer and G. S. Debarati, “Natural disasters, armed conflict, and public health,” *The new England Journal of Medicine*, vol. 369, no. 19, pp. 1836–1842, 2013.

[10] R. G. Jeremy, N. W. Kim and L. E. Shandell, “Disaster preparedness among health professionals and support staff: What is effective? An integrative literature review,” *Prehospital and Disaster Medicine*, vol. 32, no. 3, pp. 1–7, 2017.

[11] Z. Sarah, “Women’s, children’s, and adolescents’ health in humanitarian and other crises,” *BMJ*, vol. 351, Suppl1, pp. 56–60, 2015.

[12] Y. Takeo, U. Shigeru and I. Tadashi, “Care of children in a natural disaster: lessons learned from the great east Japan earthquake and tsunami,” *Pediatric Surge International*, vol. 29, pp. 1047–1051, 2013.

[13] G. Martin, W. Andreas and V. S. Johan, “Foreign field hospitals after the 2010 Haiti earthquake: How good were we?” *Emergent Med Journal*, vol. 30, no. 8, pp. 1–5, 2013.

[14] WHO Collaborating Centre for Research on the Epidemiology of Disasters (CRED), 2018 Review of Disaster Event. EM-DAT. 2019. [Online]. Available: http://www.emdat.be/#paper.

[15] H. K. M. Mohammad, S. Masoud and E. Ali, “Major earthquakes of the past decade (2000–2010): A comparative review of various aspects of management,” *Trauma Monthly*, vol. 17, no. 1, pp. 219–229, 2012.

[16] A. Grigoris, G. Paul and V. H. Frank, *A Semantic Web Primer*, PHI Press, India, 2012.

[17] Z. Hu, J. Li and H. Yu, “Modeling of clinical pathways based on ontology,” in *Proc. of the Second IEEE. Int. Conf. on IT in Medicine& Education*, pp. 1170–1174, 2009.

[18] H. T. Virkki and G. L. L. Reniers, “A case-based reasoning safety decision-support tool: Next case,” *Safety Expert Systems with Applications*, vol. 36, no. 7, pp. 10374–10380, 2009.

[19] Z. Lulu, L. Xu, and L. Youping, “Emergency medical rescue efforts after a major earthquake: Lessons from the 2008 Wenchuan earthquake,” *The Lancet*, vol. 379, no. 3, pp. 853–861, 2012.

[20] Z. Lulu, L. Yuan and L. Xu, “Rescue Efforts Management and Characteristics of Casualties of the Wenchuan Earthquake in China,” *Emerg Med Journal*, vol. 28, pp. 618–622, 2012.

[21] C. G. Miao and G. Z. Nie, “Exploration on mode of earthquake emergency command,” *Journal of Natural Disasters*, vol. 13, pp. 48–54, 2004.

[22] M. James, G. Zouris and W. Jay, “Projection of patient condition code distributions for military personnel during nonconventional operations,” *Naval Health Research Center Report*, 2001.

[23] F. H. Norris, M. J. Friedman and P. J. Watson, “60,000 disaster victims speak, Part I: An empirical review of the empirical literature, 1981–2001,” *Psychiatry*, vol. 65, pp. 207–239, 2002.

[24] S. Tao, Z. Shan and Z. H. Wang, “Afterthoughts on hospital ship during harmony mission-2015 oversea medical service,” *Military Medical Sciences*, vol. 40, no. 3, pp. 171–174, 2016 (in Chinese).