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Concept based auto-assignment of healthcare questions to domain experts in online Q&A communities

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ABSTRACT

Background: Healthcare consumers are increasingly turning to the online health Q&A communities to seek answers for their questions because current general search engines are unable to digest complex health-related questions. Q&A communities are platforms where users ask unstructured questions from different healthcare topics.

Objectives: This study aimed to provide a concept-based approach to automatically assign health questions to the appropriate domain experts.

Methods: We developed three processes for *(1) expert profiling, (2) question analysis and (3) similarity calculation and assignment*. Semantic weight of concepts combined with TF-IDF weighting comprised vectors of concepts as expert profiles. Subsequently, the similarity between submitted questions and expert profiles was calculated to find a relevant expert.

Results: We randomly selected 345 questions posted by consumers for 38 experts in 13 health topics from NetWellness as input data. Our results showed the precision and recall of our proposed method for the studied topics were between 63 %–92 % and 61 %–100 %, respectively. The calculated F-measure in selected topics was between 62 % (Addiction and Substance Abuse) and 94 % (Eye and Vision Care) with a combined F-measure of 80 %.

Conclusions: Concept-based methods using unified medical language system and natural language processing techniques could automatically assign actual health questions in different topics to the relevant domain experts with good performance metrics.

1. Introduction

Many consumers are turning to the online health resources for asking questions and improving their clinical knowledge about healthcare conditions, specifically when they are dealing with medical problems [1,2]. Consumers can freely ask their questions in such environments for awkward topics such as sex and emotional issues without any stress. Furthermore, consuming published information from reliable sources on the internet can help individuals play a more active role in their health [3–5]. There are multiple platforms such as blogs, newsgroups, social networks, and online Q&A communities where health consumers can freely exchange information or ask questions [6–8]. It has been shown that such online resources with a variety of information have great potentials for changing people's lifestyle and behavior [9–13].

The most prevalent method for seeking information on the web is to use search engines. However, sifting through search engine results to find the most appropriate answer for a medical problem is challenging. Users have to formulate complex health questions in short queries with few keywords. Previous studies have shown consumers usually enter an average of 2 or 3 terms in the web search engine forms [14–16]. However, most of the current search engines cannot respond to the complicated queries [17]. Therefore, many healthcare consumers have turned to the online Q&A communities as a preferred method of obtaining relevant information [18,19].

Q&A communities allow users to ask unstructured questions about their medical problems in natural language without any limitation. Some online health communities such as NetWellness and WebMD have millions of page visits each month. NetWellness is an online healthcare community that is founded by three universities with 500 collaborating health experts. More than 70,000 health related questions have been answered by domain experts in this platform [20]. WebMD is also one

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of the top online healthcare information services that was founded about twenty years ago with more than 100 million unique monthly visitors [21].

However, challenges still exist in Q&A communities for matching questions with appropriate experts for a given domain. The expert matching problem was introduced as a challenge in Text Retrieval Conference (TREC 2007) where various solutions based on TD, Boolean, IDF, TFIDF, and language models were presented [22,23]. There are two main steps in expert retrieval systems; *expert profiling* which includes identification of skills for an individual, and *expert selection* which emphasizes on choosing the most appropriate person among a list of qualified experts [24,25]. Expert profiling systems are considered a subclass of information retrieval (IR) methods. In the process of expert profiling, multiple resources such as publications, activities of online communities, social networks subscriptions, and educational materials can be used to enrich profiles [26,27]. Thus, a strong association to the relevant resources indicates expertise in a given topic [28].

1.1. Objectives

This study aimed to develop a concept-based framework to automatically assign health questions to the relevant domain expert in online Q&A communities.

2. Methods

The overall process of concept-based auto-assignment of health question to the related domain expert is depicted in Fig. 1. The three main sub-processes include: *(1) expert profiling, (2) new question analysis and (3) similarity calculation and assignment.* The "expert profiling" sub-process runs periodically to automatically update profiles of the experts. The "new question analysis" sub-process is executed whenever a new question submitted to an online community.

The real submitted questions to NetWellness were used in this study. All of the questions were free text questions which their answers were also free text. The quality of the questions was significantly different. Some questions were too short while some others were too long. Also, a few of included questions misspelled and had ambiguous words. Furthermore, the number of specialized terms and the level of technicality were also fluctuating. Despite such variability in the content of the questions, we did not omit any question or apply any type of filtering that may have affected our pipeline performance. The dataset of the Q&As which was used in this study is available via the supplementary file 1.

2.0.1. Expert profiling sub-process

The steps for generating a concepts-based profile for each of the experts contained three phases: pre-processing, processing, and post-processing with several sub-steps within each phase (Fig. 2).

2.0.2. Step 1: Q&A Item Separator

Q&A Item Separator module splits Q&A input to *Title, Question,* and *Answer* as pre-defined parts and stores them in a temporary pool.

2.0.3. Step 2: Text Cleaning

Text cleaning performed before the concept extraction & mapping phase and goes through three sequences to prepare unstructured questions for the NLP analysis phase.

- Special Character Removing
- None-ASCII Convertor
- Misspelled correction

2.0.4. Step 3: Concept Extraction & Mapping

For natural language processing purpose, we created a MetaMap pipeline to process each question and extract UMLS concepts. MetaMap can process the input text with different controlled vocabularies as the terminological source. We restricted the NLP pipeline to the Consumer Health Vocabulary (CHV) for mapping health consumer terms to their equivalent controlled vocabularies [29,30].

2.0.5. Step 4: Concept Semantic Weighting

MetaMap assigned a threshold number to each extracted concept up to 1000. This value indicates the coverage and centrality of the concept in the processed text of the question. We have normalized this value in the range of [0–1] and called it semantic weight.

2.0.6. Step 5: Concept TF-IDF Weighting

TF-IDF (term frequency-inverse document frequency) is a numerical

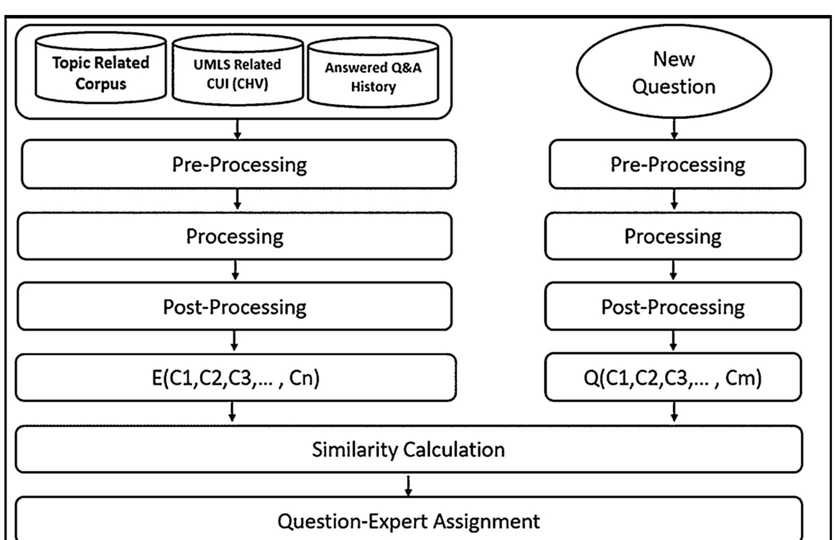

Fig. 1. The overall process of auto-assignment of concept-based question-expert.

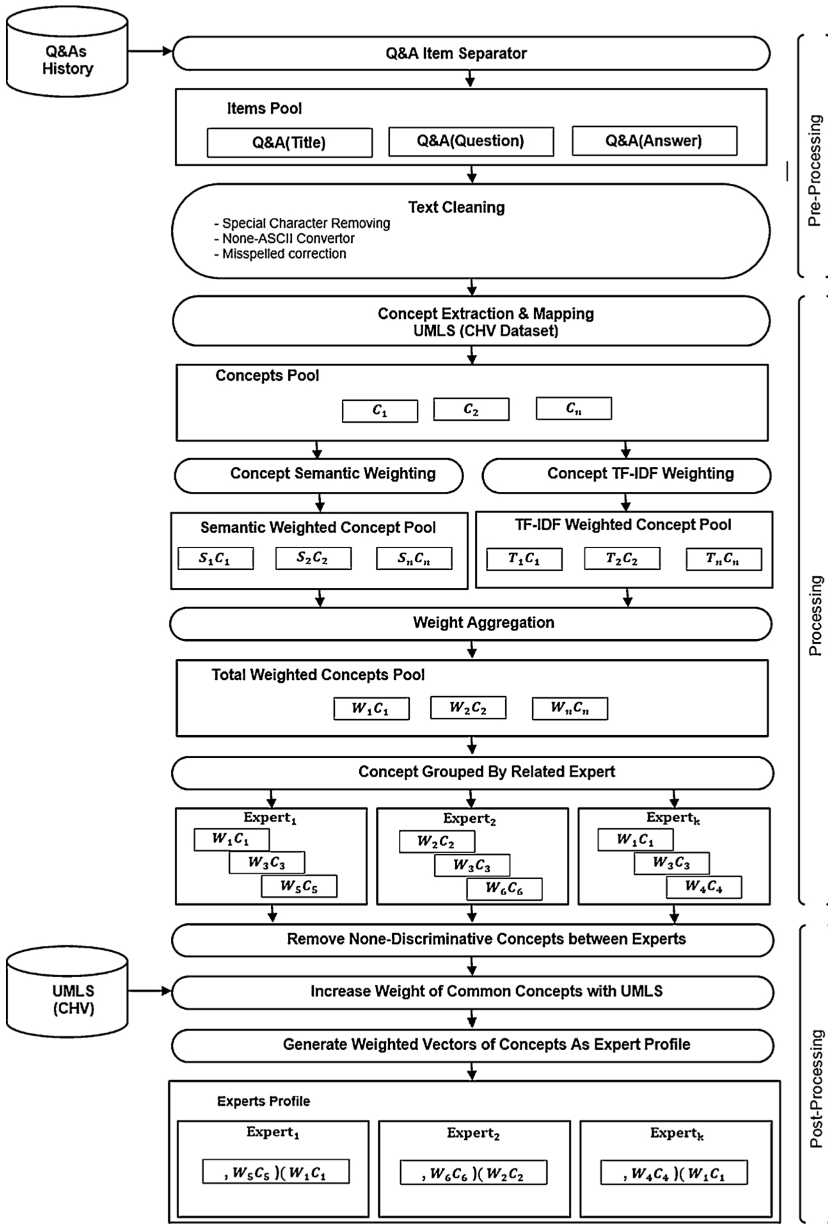

Fig. 2. The process of generating a concepts-based profile for each expert.

value that indicates the importance of a term in a collection or corpus of documents. *Term Frequency* measures the number of times that a word occurs in a document. A word that is repeated several times in a document is usually more important than a word that appears only once. *Inverse Document Frequency (IDF) is an* indicator that shows how much information a given word provides. A rare word that appears in a few documents usually has more value than a common word that happens in most of the documents. The more a word appears in a document the more the value of TF-IDF. In order to adjust the effect of general words that appear more frequently in all documents, the frequency of a given word in the corpus decreases TF-IDF value [14–1631].

$$W_{TF-IDF}(Q_i) = \frac{F_q}{\max(Q)} \times \left(\log_2 \frac{N}{N_c} + 1\right) \tag{1}$$

F_q = *Frequency of specific CUI in question* Q_i

Q = *Frequency of any CUI in question* Q_i

N = *Number of all questions*

N_c = *Number of questions contained spesific CUI*

$$W_{TF-IDF}(E_j) = \frac{F_e}{\max(E)} \times \left(\log_2 \frac{N}{N_c} + 1\right) \tag{2}$$

F_e = *Frequency of specific CUI in in all questions answered by expert* E_j

E = *Frequency of any CUI in all questions answered by expert* E_j

N = *Number of all questions*

N_c = *Number of questions contained spesific CUI*

2.0.7. Step 6: Weight Aggregation

In this step the total weight (W_i) for each concept was calculated by multiplying semantic weight (S_i) and TF-IDF weight (T_i).

2.0.8. Step 7: Concepts Grouped by Relevant Experts

After aggregating concept weight, extracted concepts from Q&As that were related to each expert were grouped in distinct partitions (expert pool). Each group contained total weighted concepts.

2.0.9. Step 8: Remove None-Discriminative Concepts among Experts

Concepts that were repeated in all expert pools were removed. These concepts were not a good discriminator for separating experts from each other.

2.0.10. Step 9: Increase Weight of Common Concepts with UMLS

For each selected topic, UMLS concept list was constructed. For this purpose, all CUIs of CHV dataset that are directly associated with every topic in UMLS were obtained as topic CUI-list. Subsequently, the weight of common concepts between expert pools and topic CUI-list was increased.

2.0.11. Step 10: Generate Weighted Vectors of Concepts as Expert Profiles

All the remaining concepts in the expert pools that were attributable to the expert profiles contained final adjusted weights from the previous steps. A higher weight of a concept in these vectors reflects the ability and experience of the expert in a given domain of healthcare.

2.1. New question analysis sub-process

The pre-processing, processing and post-processing were all done to analyze any new submitted question by healthcare consumers. These steps included:

1 Q&A Item Separator
2 Text Cleaning
3 Concept Extraction & Mapping
4 Concept Semantic Weighting
5 Concept TF-IDF Weighting
6 Weight Aggregation
7 Generating Weighted Vectors of Concepts as New Question

These methodologies for these steps are the same as the expert profiling section. The output of this sub-process was a weighted vector that contained identified concepts for a given question.

2.2. Similarity calculation and assignment sub-process

2.2.1. Step 1: Similarity Calculation

First, cosine similarity was used to calculate the similarity between the newly submitted question and all experts' profiles. Comparisons were made between the concepts in the profile of each expert and the concepts extracted from newly submitted questions (Eq. (3)). In this formula, vectors (Q and Ej) only contain common concepts between an expert profile and user query. Therefore, the dimensions of the vectors are the same.

$$Similarity(Q\ ,E_j\ ) = \frac{Q\ .\ E_j}{||\ Q\ ||\ .\ \ ||E_j\ ||} \tag{3}$$

Where Q is a weighted vector that contains extracted concepts from the newly posted questions (Eq. (4)) and E_j is the profile of $Expert_j$ (Eq. (5)), which is the result of the process depicted in Fig. 2.

$$Q = (W_1C_1\ ,\ \ W_2C_2\ ,\ \ ...,W_nC_n) \tag{4}$$

$$E_j = \ (W_1C_1\ ,\ \ W_2C_2\ ,\ \ ...,W_nC_n) \tag{5}$$

Also $||\ Q\ ||$ and $||\ E_j\ ||$ were computed by Eqs. (6) and (7) where w_i^2 is the square of weight for each concept in the vectors.

$$||Q\ || = \sqrt{\sum\nolimits_{i=1}^{n} w_i^{2}} \tag{6}$$

$$||E_j\ || = \sqrt{\sum\nolimits_{i=1}^{n} w_i^{2}} \tag{7}$$

2.2.2. Step 2: Question-Expert Assignment

This module calculated the similarity value between a newly submitted question and all experts from the previous step. First, all experts were sorted in descending order based on their computed similarity values with the new submitted question. Then, the first expert from the list who had the most similar profile to the extracted concepts from the new question was selected. Finally, the new submitted question was assigned to the selected expert to be answered. This is a one-to-many algorithm because the same expert may be assigned to another question in the future because he or she is most similar to that question.

2.3. Evaluation of the proposed method

To evaluate our method, NetWellness was considered as the source of health Q&A community for generating expert profiles. For the training and testing sets, we randomly selected 1100 questions (755 and 345 questions, respectively) from 13 health topics in NetWellness. Overall, 38 experts from 13 health domains were selected in our process. Table 1 shows testing set content in more details.

After analyzing each test question, a weighted vector that included extracted concepts from the question, was generated. Subsequently, the similarity between a given question and all expert profiles was calculated. Finally, the system automatically assigned test question to the most appropriate expert with the highest similarity value.

We considered such questions in NetWellness websites as a gold

Table 1
Distribution of the randomly selected questions for testing the proposed assignment method.

Topic	Number of experts	Number of questions	Average of question length (characters)	Average of extracted concepts from each question
Lung diseases	3	26	421.96	10.96
Diet and Nutrition	3	29	291.63	7.03
Ear, Nose, and Throat Disorders	3	30	475.47	11.57
Eye and Vision Care	3	25	573.16	15.24
Breast Cancer	3	30	440.40	11.50
Digestive Disorders	3	20	400.70	9.85
Kidney Diseases	2	20	423.42	13.30
Addiction and Substance Abuse	3	28	524.68	11.71
Dental and Oral Health (Adults)	3	30	471.23	11.23
Urinary Disorders	3	27	587.96	15.11
Sleep Disorders	3	20	512.73	17.75
Women's Health	3	30	442.97	10.50
Tuberculosis	3	30	644.47	16.70

standard and compared the results of our proposed auto-assignment method to the results of NetWellness. We found that our system would generate accurate results if the proposed method assigns test question to the same topic as NetWellness manually does such assignments.

For selected topic T, we defined:

True Positive (TP): Questions are manually assigned to topic T where our proposed method also correctly assigned question to the same topic T.

False Positive (FP): Questions are manually assigned to topics other than topic T where our proposed method incorrectly assigned questions to topic T.

False Negative (FN): Questions are manually assigned to topic T where our proposed method incorrectly assigned questions to topics other than topic T.

To evaluate our method within the domain of information retrieval system, precision, recall, and F-Measure were computed. In our method, these metrics, for the purpose of question assignment to topic T, were defined as:

Precision: How many assigned questions to the topic T were relevant to this topic.

Recall: How many relevant questions to the topic T were assigned to this topic.

Eqs. (8) and (9) show how precision and recall are calculated.

$$precision = \frac{TP}{TP + FP} \tag{8}$$

$$recall = \frac{TP}{TP + FN} \tag{9}$$

Precision and recall can be combined together and generate a harmonic balance, known as F-Measure. This measure indicates the accuracy of our method and can be formulated as follows:

$$F - measure = 2\,.\,\frac{precision\,.\,\,recall}{precision + recall} \tag{10}$$

3. Ethical considerations

This study has not involved the human and animal subjects.

4. Results

Table 2 shows the characteristics of the questions included in this study. The Q&As were free text and they could have any length without limitation.

Table 3 shows the similarity between the different health topics. The table clearly shows that the similarity between questions from same topics (intra-topic similarity) is significantly higher than the similarity between questions from different topics (inter-topic similarity). For example, the similarity within the questions of "Sleep disorder" was 0.81 but the similarity between "Sleep disorder" and "breast cancer" was 0.05. 'Sleep disorder', 'Eye and vision care', and 'breast cancer' topics had the most intra topic similarity, respectively.

Evaluation results for the proposed question-expert auto-assignment method are listed in Table 4. The accuracy and recall of our proposed method for the studied topics were in the range of 63 %–92 % and 61 %–100 %, respectively. Evaluation results from our system showed the highest precisions in 'Eye and Vision Care', 'Breast Cancer' and 'Ear, Nose, and Throat Disorders' topics and lowest precisions in 'Addiction and Substance Abuse' and 'Digestive Disorders' topics. Also, the highest recall values were seen in 'Sleep Disorders', 'Eye and Vision Care' and 'Breast Cancer' topics, respectively. The lowest recall values belonged to 'Addiction and Substance Abuse' and 'Women's Health' topics. F-measure metric in selected topics was between 62 % (Addiction and Substance Abuse) and 94 % (Eye and Vision Care).

Table 2
Descriptive statistics for character length of Q&As.

Length	Train Questions (755)			Test Questions (345)		
	Title	Question	Answer	Title	Question	Answer
Min	2	5	26	4	5	51
Max	63	3576	8835	69	3112	10122
Average	24.7	536.3	954.4	25.6	500.3	923.3
Standard Deviation	11.2	439.1	965.1	11.4	410.8	1045.7

Fig. 3 shows the distribution of question-expert assignment in selected topics where our method correctly (or incorrectly) assigned questions to each topic. For example, in the Lung diseases topic, 69.23 % of questions were correctly assigned to its topic. Alternatively, our method incorrectly assigned 30.77 % of the questions to lung disease topic where they actually belonged to 'Breast Cancer' (3.85 %), 'Digestive Disorders' (3.85), 'Addiction and Substance Abuse' (7.69), 'Sleep Disorders' (3.85), and 'Tuberculosis' (11.54).

5. Discussions

In this study, we developed a concept-based approach to automatically assign health questions to the relevant domain experts. By applying clinical natural language processing methods, we were able to extract and map concepts to the Consumer Health Vocabulary (CHV) terminology. Also, semantic and TF-IDF weighting methods were combined to create concepts vectors as expert profiles. Finally, the similarity between submitted question, by healthcare consumers, and expert profiles were calculated for matching to the most appropriate healthcare expert.

Expert profiling can be performed by explicit and implicit methods. In an explicit profiling approach, expertise is advocated by healthcare experts themselves. However, in implicit profiling methods, activities of experts in online resources are automatically extracted and analyzed. People's experience, skills, and knowledge can change over time. There is a significant challenge in explicit profiling since individuals do not have enough motivations to update their online profiles [32]. Therefore, automated methods based on information retrieval techniques can be used to update profiles implicitly within online communities as well as interactive collaboration spaces such as online forums [29,30,33]. In the proposed method, a combination of both approaches was used. Educational records of a given expert, that were declared by him/herself explicitly, were considered as base concepts of the expert's profile. Subsequent processing and concept extraction of Q&As that are relevant to each expert will implicitly upgrade expert profiles periodically.

In our method, different terms that were pointing to the same meaning were mapped to a UMLS standard concept. Therefore, for each extracted concept a semantic weight was computed based on the coverage and centrality of the term. Also, considering the number of times a term appears, for each concept, a TF-IDF weight was calculated to adjust the effect of generally appearing words. The level of expertise is changing over time, thus, the expert profiling process should be updated periodically. In Q&A communities, the number of questions and answers will increase over time. As a result, TF-IDF weighting and other processing steps described in our method should be running in the background in order to keep the expert profiles up-to-date.

It has been shown that there is a gap between clinical terms used by healthcare professionals and consumers, which can potentially decreases the accuracy of automatic question-to-expert assignment systems [34,35]. Also, there is a challenge in analyzing health-related Q&As text that contain abbreviations, acronyms, and misspellings. Another study showed that the automation expert profiling process can be improved by using controlled vocabularies [36]. We have shown that Consumer Health Vocabulary (CHV) can be used as the knowledge source in the processing steps of our proposed method. CHV contains a comprehensive list of commonly used terms by healthcare consumers including misspellings and ambiguous terms. Consistent mapping of

Table 3
Concept-based similarity of the questions (Intra and inter topic similarity).

	Breast Cancer	Dental and Oral Health (Adults)	Diet and Nutrition	Digestive Disorders	Ear, Nose, and Throat Disorders	Eye and Vision Care	Kidney Diseases	Sleep Disorders
Breast Cancer	**0.62**	0.11	0.07	0.12	0.11	0.07	0.12	0.05
Dental and Oral Health (Adults)		**0.49**	0.06	0.10	0.18	0.08	0.10	0.12
Diet and Nutrition			**0.50**	0.16	0.06	0.05	0.10	0.08
Digestive Disorders				**0.33**	0.14	0.09	0.18	0.10
Ear, Nose, and Throat Disorders					**0.43**	0.15	0.12	0.12
Eye and Vision Care						**0.63**	0.08	0.09
Kidney Diseases							**0.61**	0.08
Sleep Disorders								**0.81**

Bold value show the similarity of each topic with itself.

Table 4
Evaluation results for the proposed question-expert auto-assignment method.

Topic	Count	TP	FP	FN	Precision	Recall	F-measure
Lung diseases	26	18	3	8	0.86	0.69	0.77
Diet and Nutrition	29	24	3	5	0.89	0.83	0.86
Ear, Nose, and Throat Disorders	30	23	3	7	0.88	0.77	0.82
Eye and Vision Care	25	24	2	1	0.92	0.96	0.94
Breast Cancer	30	28	3	2	0.90	0.93	0.92
Digestive Disorders	20	16	9	4	0.64	0.80	0.71
Kidney Diseases	20	14	6	6	0.70	0.70	0.70
Addiction and Substance Abuse	28	17	10	11	0.63	0.61	0.62
Dental and Oral Health (Adults)	30	27	4	3	0.87	0.90	0.89
Urinary Disorders	27	21	4	6	0.84	0.78	0.81
Sleep Disorders	20	20	6	0	0.77	1.00	0.87
Women's Health	30	20	5	10	0.80	0.67	0.73
Tuberculosis	30	25	10	5	0.71	0.83	0.77

jargons used by healthcare consumers to standard vocabularies is facilitated by CHV dataset in order to reduce the gap between the language of healthcare consumers and providers [37–40]. we think that UMLS/CHV would have better performance than other controlled vocabularies such as NCI Thesaurus and SNOMED-CT. However, this should be investigated by performing another study and implementing different vocabularies in the proposed approach with the aim of comparing the role of the other controlled vocabularies with UMLS.

We evaluated our method with the actual submitted questions (available in supplementary file 1) to the NetWellness community and compared our assignment results with manually pre-assigned question by subject matter experts. Some NetWellness health topics, that may have included subtopics, were too general. Also, the overlap among the concepts of some of the NetWellness topics were too large that may have caused an increase in the number of false negative or positive results. For example, 'Addiction and Substance Abuse' is a general topic with no specific concepts attached to it. Therefore, precision, recall and F-measure obtained for this topic was typically lower than other topics. On the other hand, topics such as Eye and Vision Care', 'Breast Cancer', and 'Adult Dental and Oral Health' that contained more specific and discriminative concepts, were reported with higher precision, recall and f-measure. When we see the Tables 3 and 4 together, it is quite clear that the 'Sleep Disorder, 'Eye and Vision Care', and 'breast cancer' topics which had the most intra-topic similarity also had the highest recall values.

Evaluation results showed that our proposed framework, with an acceptable overall F-Measure of 0.8, can automatically assign submitted healthcare questions by consumers in real time to the relevant domain experts. Also, our observation points to the fact that the performance of such auto-assignment increases in specific health topics.

6. Conclusions

Concept-based method using UMLS and NLP techniques could automatically assign actual health questions in different topics to the relevant domain experts with good performance metrics.

7. Limitation

Our analysis was limited only to a few health Q&A topics. Although, such topics were selected randomly, including questions from a wider range of health topics can lead to a more comprehensive and generalizable results. Furthermore, we did not consider different implementation of the proposed method. In other words, using another tool instead of MetaMap and also changing the UMLS/CHV with the other vocabularies could have effect on the performance of the proposed method.

Author statement

Hamind Naderi: Drafting the first version of the manuscript; Reviewing the manuscript; Approved the submitted version; Designing the study; Data Analysis

Behzad Kiani: Reviewing the manuscript; Study Design; Approved the submitted version; Data Analysis.

Sina Madani: Reviewing the manuscript; Approved the submitted version; Drafting the manuscript.

Kobra Etminani: Reviewing the manuscript; Study Design; Approved the submitted version.

Ethical approval

The ethics committee of Mashhad University of Medical Sciences approved this study REC number: 951317

Guarantor

KE

Contributor ship

HN wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

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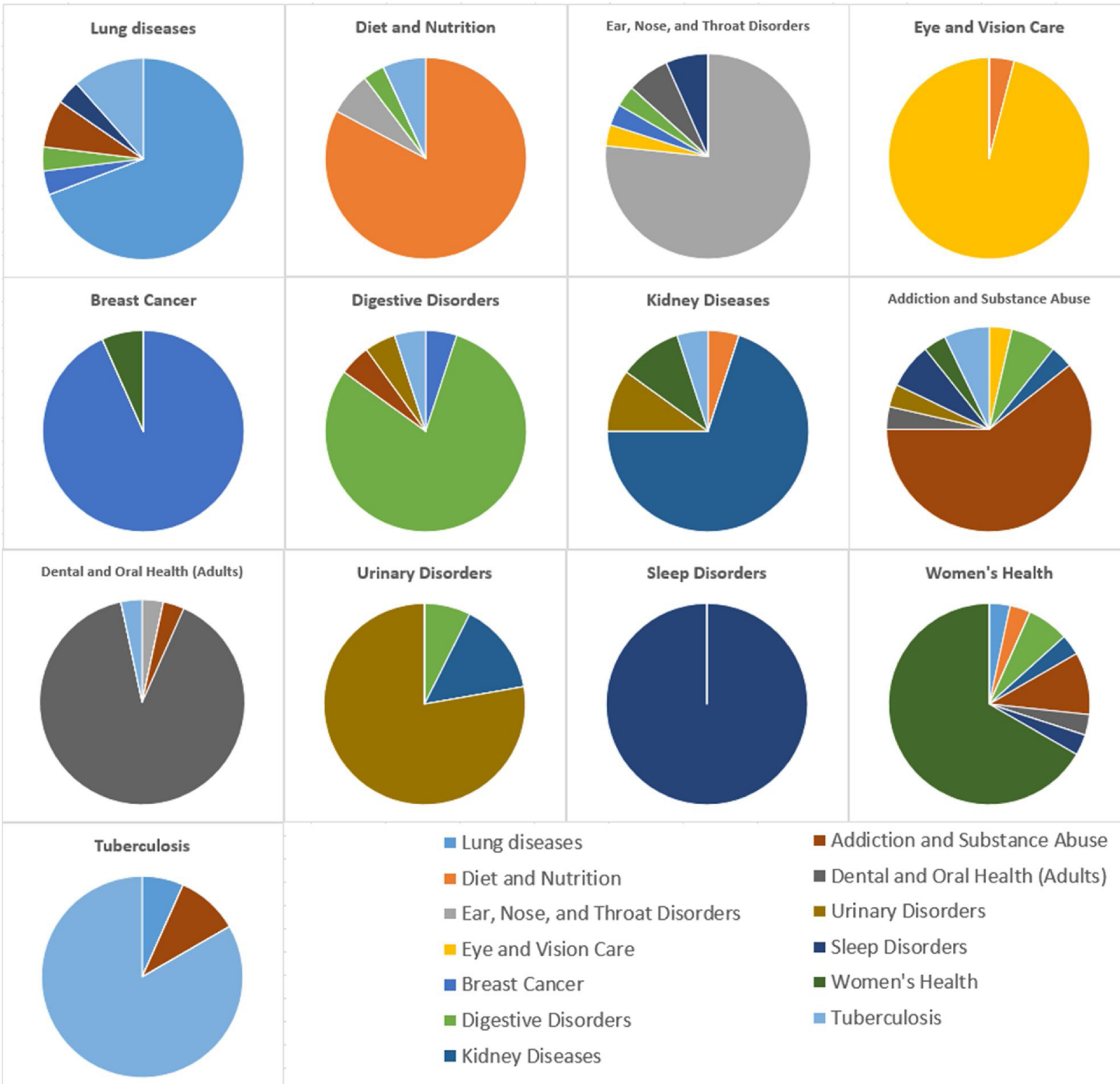

Fig. 3. Distribution of question-expert assignment in selected topics.

Summary points:

- Using UMLS and NLP techniques together could develop a powerful tool for assigning medical questions to domain experts.
- Using concept-based auto assignment of medical questions to domain experts shows different precisions for different medical domains. I.e. questions related to 'eye and vision care' has the most precision but for 'addiction and substance abuse' the least precision is obtained.
- Using concept-based auto assignment of medical questions to domain experts shows different recalls for different medical domains. I.e. questions related to 'sleep disorders' has the most recall but for 'addiction and substance abuse' the least recall is obtained.

Declaration of Competing Interest

There is no conflict of interest to be declared.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijmedinf.2020.104108.

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