Evaluating the Relevance of UMLS Knowledge Base for Public Health Informatics during Disasters

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ABSTRACT

During disasters public health organizations increasingly face challenges in acquiring and transforming real-time data into knowledge about the dynamic public health needs. Resources on the internet can provide valuable information for extracting knowledge that can help improve decisions which will ultimately result in targeted and efficient health services. Digital content such as online articles, blogs, and social media are some of such information sources that could be leveraged to improve the health care systems during disasters. To efficiently and accurately identify relevant disaster health information, extraction tools require a common vocabulary that is aligned to the health domain so that the knowledge from these unstructured digital sources can be accurately structured and organized. In this paper, we study the degree to which the Unified Medical Language System (UMLS) contains relevant disaster, public health, and medical concepts for which public health information in disaster domain could be extracted from digital sources.

Keywords

Public health, disaster informatics, health informatics, UMLS, metathesaurus.

INTRODUCTION

During disasters, international and national public health organizations increasingly face challenges in acquiring and transforming real-time data from online digital sources such as social media into knowledge about the health facility availability, disease outbreaks, and changing public health needs (Chan and Purohit 2020). These challenges prevent effective coordination of health response services and stewardship of scarce resources. For example, maintaining awareness of health facilities status (e.g., hospital power outages, damaged clinics) requires continuous information monitoring (Texas Department of State Health Services 2018). Such knowledge extracted from these online data sources can help improve decisions that can ultimately result in targeted and efficient health services. Such critical data may exist in non-traditional sources of social media platforms like Twitter, Facebook, and Reddit (Lauren 2018), where previous studies have shown that social media contains timely and relevant information to provide situational awareness for response during disasters (Houston et al. 2015; Reuter and Kaufhold 2018). Health focused governmental and non-governmental organizations have often sought improved capabilities to integrate non-traditional data sources into decision making processes (Texas Department of State Health Services 2018), however, struggled to resolve a common terminology for information management.

While the need for improved knowledge engineering during disasters is well known (Zhang et al. 2002) what has resulted in the digital information age has been an explosion of information from unstructured data sources. Information overload is a commonly cited challenge in disaster response where the influx of data and information is not met with effective information and knowledge management systems that can assist in making the data or information meaningful or useful for decision support. Standardized structures and schemas for organizing information in these systems are needed (De Nicola et al. 2020), which can ultimately support a user in the disaster

management agencies to methodically search, organize, and present information for any operational task.

Table 1. Examples of unstructured social media posts that need to be transformed to some structured form for efficient information and knowledge management of agencies focused on health response.

	Tweet
1	Another #HurricaneHarvey infectious disease risk to consider is rodent borne infections like leptospirosis
2	Diarrheal illnesses & skin infections are likeliest to spread in contaminated floodwaters #HurricaneHarvey

The Unified Medical Language System (UMLS) is a collection of standardized vocabularies and software brought together to form a unified biomedical information system (Bodenreider 2004). The UMLS contains vocabulary from more than a hundred source vocabularies, some in a number of languages. Although UMLS is comprehensive in clinical vocabularies, it is observed to lack certain words and phrases used commonly in health narrative text such as web blogs and emails. Research has shown that it is often incomplete, citing that up to 20-25 percent of health expressions by laypersons were not covered by professional health vocabularies (Zeng et al. 2002; Zeng and Tse 2006).

Identification of healthcare terms in social media poses even more challenges mainly due to the ambiguity of terms used in the user-generated text (Chan and Purohit 2020). In order for disaster related social media information to be useful for disaster health responders, the technical capabilities of computers and the vocabulary systems that they use to mine relevant social media information must be sensitive enough to retrieve concepts and terms that are used among three key groups that communicate this information during disasters: 1) medical and public health providers, 2) disaster responders, and 3) the public. Previous studies have shown that laypersons may describe clinical conditions differently (e.g., nosebleed vs. epistaxis) (Keselman et al. 2008). While public health providers and disaster responders may use similar terms such as 'disease outbreak', there are other terms, for vulnerable groups, and relationships that are unique to disasters such as child militia, unaccompanied minors, and water sanitation and hygiene (WASH). For example, a given term may have multiple meanings in different contexts (Murphy and Barnett 1996). Furthermore, the context of the terms in user-generated text on social media may not relate closely to only one definition of the term as understood by the disaster responders or public health professionals. Additionally, terms used in social media are different from the ones used in formal documents in the health domain (Keselman et al. 2008; Zeng and Tse 2006).

Examples in Table 1 illustrate two tweets (i.e., unstructured text) on disaster related health issues. There is a need for converting these unstructured text forms to structured forms with the help of medical knowledge bases for improving the machine understanding. A subtask of this process is to analyze the words and phrases in tweets to find the relevant concepts from the knowledge base. The terms *infectious* and *leptospirosis* have closely related concepts in UMLS. Therefore, those words can be easily mapped to a UMLS concept. However, the term *rodent-borne* has only a distantly related term in the UMLS vocabulary. Nevertheless, it is equally important to identify the concepts of terms missing in the vocabulary of UMLS. Additionally, words such as *infectious* and *leptospirosis* in the Tweet 1 in Table 1 yields more than one matching concept from UMLS. Therefore, it raises the question whether the UMLS vocabulary is sufficient for analyzing social media content.

In this exploratory study, we investigate how the commonly used terms in the disaster health domain for response map to Concept Unique Identifiers (CUIs) in the UMLS, and to what extent these terms align with existing concepts in the UMLS. The hypothesis is that the majority of lexical strings or terms will map to the UMLS, but a relevant minority of terms will not exist in the UMLS knowledge base. In addition, other terms will have erroneous relationships and a few terms will neither exist in the UMLS nor map to concepts. If the hypothesis is confirmed, this preliminary work will highlight the needs for future scientific advancement to either establish a more comprehensive ontology or vocabulary, or advance scientific methods to improve information extraction techniques to build a more robust knowledge base for use during disasters. The ultimate consequence will be a knowledge engineering direction to improve the information systems designed to support health-focused response operations in the future.

Paper Organization: The rest of this paper is structured as follows. The related work section includes a brief description of the background work that uses UMLS. In the methodology section, we describe the approach used for extracting concepts of disaster health terms. The results and discussion section presents the results of our analysis and provides an extensive discussion. The final section concludes our paper with a summary and future work.

Table 2. The list of concept attributes obtained from UMLS REST API

	Type of Attributes	Description
1	CUI	Concept Unique Identifier – a unique identifier for each concept in Metathesaurus.
2	SemType	A list of Semantic Types
2	AUI	Atom Unique Identifier – Atoms are the basic building blocks of Metathesaurus that identifies lexical units of each vocabulary uniquely (similar lexical unit in different vocabulary will get different unique AUIs).
3	Definition	All definitions of a known CUI (when available)
4	RSAB	Source vocabulary

RELATED WORK

Metathesaurus is a part of UMLS that provides a large biomedical thesaurus that is organized by concepts while linking concepts of different vocabularies that has the same meaning (Bodenreider 2004). This resource has been utilized by many in the biomedical field for different applications from extracting terminologies (Amos et al. 2020) to making chatbots for medical domain (Kazi et al. 2012). Majority of prior work utilized UMLS for processing text to extract concepts, relationships, or knowledge (Amos et al. 2020). Moreover, while the majority of work maps formally written text documents as the source to obtain the target concepts, there is still a lack of extensive exploration on extracting concepts from informal text documents such as social media and user-generated text across a variety of application domains (Amos et al. 2020).

To understand the gap between the understanding of health-related terms by health professionals and consumers, Keselman et al. (2008) analyzed terms that could not be mapped to UMLS concepts. They identified 64 unmapped concepts and 17 of them were considered layperson terms that could not be included in UMLS terms. Hence, we can infer that a considerable number of terms may not be found in UMLS. However, Keselman et al. (Keselman et al. 2008) were particularly interested in analyzing terms that could not be mapped to the UMLS concepts rather than the terms that were partially mapped.

Chen et al. (2018) proposed a Machine Learning-based approach based on Knowledge-Involved Topic Modeling for analyzing posts on online health communities. Although this work is using community-generated posts, they are based on a health-specific online community. Moreover, approaches that use deep neural networks have shown good performance in health related entity recognition and entitiy linking. The state of the art approaches using medical word embeddings and sentence embeddings were introduced in the recent years to determine the health related concepts in scientific pubilications and electronic health record data (Murty et al. 2018). However, the data from health specific forums are not specific to diaster domain. Therefore, it may still need fine-tuning for analyzing data in disaster context. Jimeno-Yepes et al. (2015) have created a dataset and an approach for recognizing concepts relating to diseases, drugs, and symptoms in Twitter. However, it is only applicable to those concepts and may need adjustments when trying to analyze data generated during disaster events such as hurricanes and floods.

While many have studied the use-cases of UMLS in different domains, there is still a gap of terms used professionally and by laypersons when it comes to domain-specific vocabularies, in particular for disaster management. Our focus in this study is to analyze that gap for public health informatics during disasters.

METHODOLOGY

The aim of our approach is to map disaster health and humanitarian health terms and relationships to the UMLS using the Metathesaurus. In order to map or assess the occurrence of these terms and related concepts within the UMLS, a pre-existing set of terms were selected from prior published studies and disaster management guidebooks that reflect both US and global disaster environments. The inclusion criteria were the presence of a term in two or more instances in disaster manuals, guidebooks, or protocols, or terms acquired through inductive and reductive qualitative methods for code assignments, based on a previous study of humanitarian health situation reports from the 2010 Haiti Earthquake (Chan et al. 2019). Twenty-four terms were purposively sampled from the composite term list and used in the analysis by an expert in public health informatics, emergency medicine, and disaster management. We limited to the scope to a small set of input terms, given we required an exhaustive

review of all the output by the UMLS REST API with a human expert. Six existing vocabularies were selected for analysis, including SNOMEDCT_US, MSH, HL7V3.0, WHO, LNC, and MEDLINEPLUS based on the responses from the UMLS as detailed next.

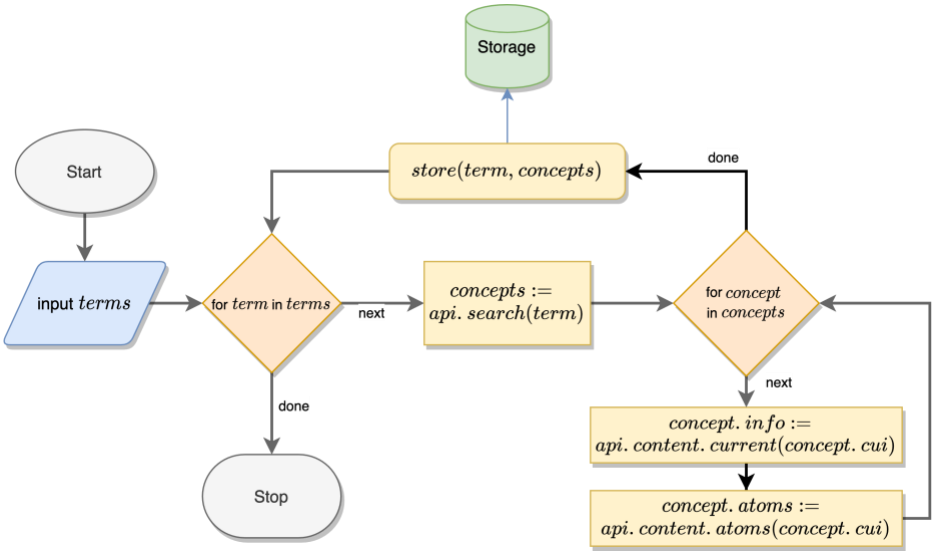

Figure 1. Algorithm for extracting concepts using UMLS REST API

For each selected disaster health term, the UMLS REST API was used to obtain specific attributes listed in Table 2. Results were evaluated by an expert in public health informatics, emergency medicine, and disaster management. The set of retrieved CUIs for a term was analyzed to determine the degree of relevance to the disaster domain-specific context of the term. Each returned CUI was assigned a relevance category using the following assignments: 1) *Exact* - when the relevance of the retrieved CUI perfectly matches the context of the domain term, 2) *Partial* - when the relevance of the retrieved CUI does not match the context of the domain term, and 3) *Missing* - when there is no retrieved CUI for the domain term. All Concept Unique Identifiers (CUIs) were considered in the analyses, and the first four atoms if present were included in the analyses based upon the return order in the UMLS REST API.

Figure 1 illustrates the algorithm for extracting required information from UMLS for an input term. The overall process takes the terms as the input and provides a list of concepts for each term as the output. Specifically, we first use the search endpoint of UMLS REST API to obtain the concepts. We specify the parameter *'sabs'* (source vocabularies) to SNOMEDCT_US, MSH, HL7V3.0, WHO, LNC, and MEDLINEPLUS to filter out other vocabularies that we are not interested in (therefore reducing the information overload). Additionally, to obtain more information about each CUI and to obtain atoms associated with each CUI we use the 'content endpoint' service of UMLS REST API. Input to the 'content endpoint' is CUI of a concept obtained through search endpoint.

Terms	CUI_Name	CUI_Code	SemType_0_name	SemType_0_code	SemType_1_name	SemType_1_code	Definition	Definition_Source	AUI_0_code	AUI_0_name	AUI_1_code	AUI_1_name	AUI_2_code	AUI_2_name	AUI_3_code	AUI_3_name	RSAB
	Concept Name	Concept Unique Identified (code)	Semantic Type Name	Semantic Type Unique Identifier (code)	Semantic Type Name	Semantic Type Unique Identifier (code)	Definition provided by available vocabulary	Vocabulary set name	Atom unique Identifier	Atom Name	Atom unique Identifier	Atom Name	Atom unique Identifier	Atom Name	Atom unique Identifier	Atom Name	Vocabulary set name
Access - general	General-IV access	C3842042	Finding	T033					A24098522	General-IV access							LNC
Access - general	Registration for online access	C4303984	Health Care	T058					A27780356	Registration for online access to	A27769206	Registration for					SNOMEDCT_US
Access - general	Registration for online access	C4303985	Finding	T033					A27788853	Registration for online access to	A27774836	Registration for					SNOMEDCT_US
Acute respiratory Illness [health risks]	No Results																
Burial Practices/Managemen	No Results																
children	Febrile infection related epilepsy	C4049262	Disease or	T047			This syndrome describes an explosive-onset	SNOMEDCT_US	A28468920	Acute encephalitis with	A28439567	DESC (devast	A28402655	FIRES -	A28420093	Febrile infectio	SNOMEDCT_US
children	CVLT-C (California	C1879984	Intellectual Product	T170			Provides a short, individually administered	NCI	A27771010	CVLT-C (California	A27767294	California Verbal	A27787468	California	A27776616	California	SNOMEDCT_US

Figure 2. Snapshot of sample output of the intermediate steps of the proposed approach containing different attribute columns for the input terms provided.

Table 3. The list of terms with unique exact matches (*Number of Terms: 13*)

Disaster Health Terms

children
community health centers
Coordination
Displacement
evacuation
famine
hurricanes
malnutrition
Protection
refugees
shelter
tornadoes
vulnerable populations

RESULTS AND DISCUSSION

Executing the UMLS REST API on the identified health disaster terms resulted in 492 CUIs. Figure 2 illustrates a snapshot of sample output of the intermediate steps of the proposed approach containing different attribute columns for input terms provided. The results were analyzed by a credible expert with the credentials of Doctor of Medicine (MD) who works closely with humanitarian organizations.

Table 4. Disaster health domain terms for which there was at least one exact match.

Term	CUI Name	CUI Code	Name of SemType 0
children	Child	C0008059	Age Group
community health centers	Community Health Centers	C0009469	Health Care Related Organization
Coordination	coordination of care	C4724363	Health Care Activity
Displacement	Qualitative Displacement	C0456080	Qualitative Concept
evacuation	Emergency Shelter	C3178959	Manufactured Object
famine	Famine	C0015619	Phenomenon or Process
hurricanes	Hurricanes	C0020183	Natural Phenomenon or Process
malnutrition	Child Malnutrition	C1257753	Disease or Syndrome
Protection	Referred to social services for adult protection	C1562621	Health Care Activity
refugees	Refugees	C0034961	Population Group
shelter	Emergency Shelter	C3178959	Manufactured Object
tornadoes	Tornadoes	C0040476	Natural Phenomenon or Process
vulnerable populations	Vulnerable Populations	C0949366	Population Group

Table 5. Examples of terms with the retrieved CUIs for irrelevant concepts (partial match).

Term	CUI Name	CUI Code	Name of SemType 0	Disaster Health Domain Definition

Coordination	Cerebellar Ataxia	C0007758	Disease or Syndrome	coordination in disasters is a healthcare activity and not a sign of a clinical disease.
Displacement	Hip Dislocation	C0019554	Injury or Poisoning	displacement refers to the voluntary or forced displacement of individuals during disasters (ReliefWeb 2008)
evacuation	Incision and drainage	C0152277	Therapeutic or Preventive Procedure	Therapeutic or Preventive Procedure Security measure to clear a region of its inhabitants generally under threat, which involves the collaboration of civil society at an individual or group level. (ACAPS 2015)
Protection	Foot protection	C0337164	Manufactured Object	A concept that encompasses all activities aimed at obtaining full respect for the rights of the individual in accordance with the letter and spirit of human rights, refugee and international humanitarian law. (ACAPS 2015)

Of the 24 disaster health domain terms entered into the Metathesaurus, 54% (n=13) of all terms resulted in at least one CUI with an exact relevance assignment (see Table 3 for terms that resulted in unique exact matches). Among the 492 CUIs, only 16% (n=79) had an exact relevance assignment. A large proportion of the other returns were irrelevant to the term as it would be applied in the disaster health domain.

Exact Matches

Table 4 illustrates the disaster health domain terms for which there was at least one exact match, and their respective CUI codes, names and semantic types. The terms related to disaster events such as tornadoes and hurricanes and population groups such as children and refugees were retrieved which are important for information systems to support operational decision making. There were also exact returns for specific places or facilities for which health services or disaster services are frequently provided during a disaster event such as community health centers and shelter.

Partial Matches

A larger percentage of CUI returns for each disaster health term were assigned a partial match relevance and further sub-categorized as relevant to the disaster health domain or irrelevant to the domain, where the relationship would be judged based on the potential relevance for the coordination of health services in the disaster response operations. Figure 3 shows the patterns of partial-relevant and partial-irrelevant returns for each term.

For example, while the disaster domain term “children” may have an exact match as seen in Figure 3 the majority of the other CUI returns for that term are partial and irrelevant. Similar trends are seen for displacement, protection, evacuation, and coordination. Table 5 provides examples of partial irrelevant CUIs and the semantic types of the retrieved terms/returns. This can be largely due to the ambiguity of the terms in different contexts.

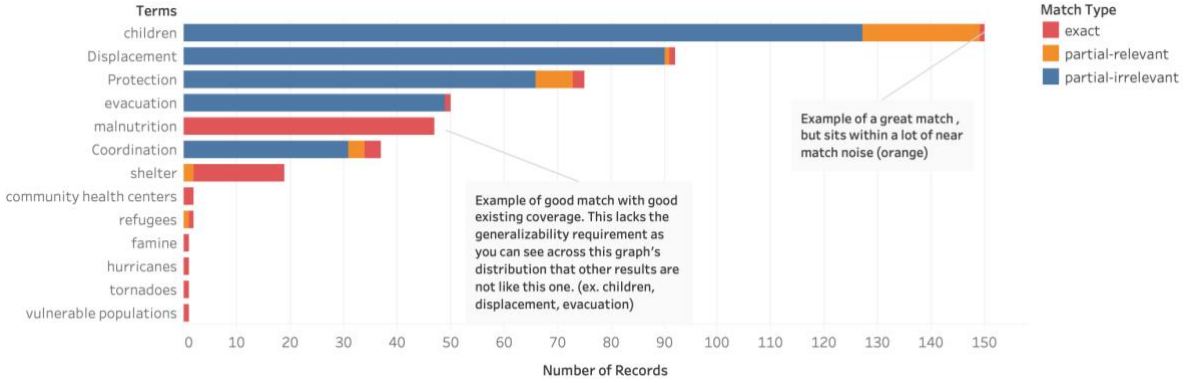

Figure 3. Patterns of returns from CUIs (N=492)

Missing Concepts

We have observed 33% (n=8) of all terms that do not match with any concept in the UMLS. Our hypothesis was that a minority of terms would not end up retrieving any concepts from the UMLS. This hypothesis in the preliminary purpose sample was confirmed, where we found this pattern to be more noteworthy than previously published findings from other disciplines such as Consumer Health Vocabularies (CHV) (Keselman et al. 2008). Lists of terms that do not have any retrieved concepts from UMLS REST API is as follows: Water/Sanitation (WASH), Road access, Medical Logistics-distribution, Emergency Operations Center (EOC), Damaged health infrastructure, Complex emergency, Burial Practices/Management, Acute respiratory illness (health risks).

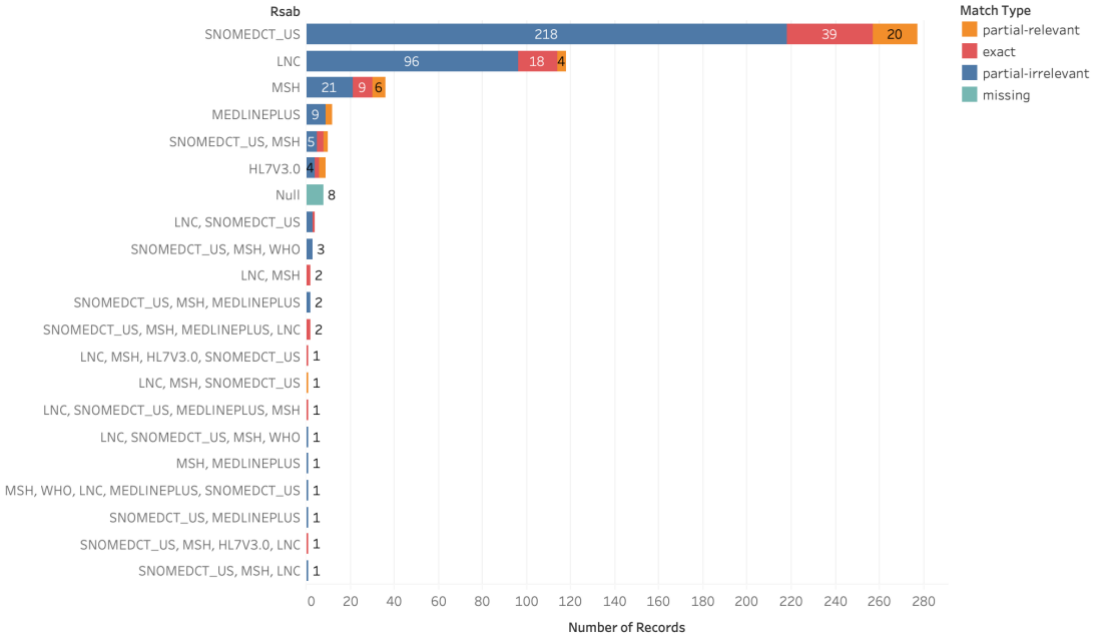

Figure 4. Distribution of Match type by Vocabularies

Individual Vocabulary Performance

In this subsection we analyze the performance of an individual term's retrieved concept CUIs, for the UMLS vocabularies. Figure 4 shows the specific vocabulary performance. We note that the Logical Observation Identifiers Names and Codes terminology (LNC) vocabulary (that provide formal names and standardized codes for laboratory and other clinical observations) has a wider coverage. Therefore, it will be a good candidate to review the underlying data for the input terms and corresponding retrieved concept CUIs, as well as the domain relevance/match label assignment to better determine the significance of such types of vocabulary in the UMLS knowledge base from the disaster management viewpoint. We also note that there is less overlap between included

vocabularies that no single vocabulary would provide the necessary CUIs to meet the needs of the disaster health domain.

CONCLUSIONS

This paper explored the potential use of standardized vocabularies of UMLS knowledge base for information management systems to support the decision makers in governmental and non-governmental organizations regarding health-focused response during disasters. We have assessed the relevance of UMLS vocabulary for the recognition of public health terms commonly used by the general public during disasters. We selected 24 expert-derived health terms related to disaster domain for our analysis. Next, each term's retrieved concept/CUI extracted from UMLS is labelled with relevance levels based on an expert's experience in public health, emergency medicine, and disaster management. Then the evaluation was carried out with respect to the unique exact matches, overall exact matches, missing returns, partial matches and individual vocabulary performance. We found that many of the concepts in the existing ontologies and vocabularies of UMLS are not aligned with the disaster domain terminology resulting in a large percentage of "noise" or irrelevant and missing concepts, when retrieving the concepts from the knowledge base for a domain term. These preliminary results motivate a need for extending the ontologies and knowledge base of UMLS to enable accurate structured representation of unstructured data from various data sources in the disaster domain. Such structured organization of information could then timely provide information to decision makers in standardized format, being consistent with the existing structured representation of information in the current information systems for disaster management with a health-focused response. Further studies are also needed to determine how Natural Language Processing (NLP) methodologies in Artificial Intelligence can improve the retrieval of relevant concept CUIs from UMLS knowledge base by leveraging approaches beyond the lexical term matches, especially in the narrative text of social media with several grammatical errors and abbreviations.

We acknowledge a few limitations of this study given the preliminary exploratory work. First, the sample size of the set of disaster domain terms queried for UMLS REST API is small, which was partly due to the involvement of a human expert to judge the relevance of the API output exhaustively. In the future work, we plan to expand the study with the crowdsourcing platform where the users may not be experts, by consulting with our expert evaluator on designing such a study using a crowdsourcing platform for relevance judgement. Second, we were limited to the retrieval of concept CUIs from UMLS through its REST API only, which could be further improved with additional NLP approaches to improve the recall of the retrieved set of concepts from the knowledge base. Lastly, we explored the disaster domain terms sampled from the prior literature in the public health and crisis informatics, which could be future expanded to incorporate frequent terms from the additional data sources such as user-generated content on social media shared during the recent crises that are not just natural hazards, for instance, the ongoing COVID-19 pandemic.

REPRODUCIBILITY

The code and related data of this study are available at https://github.com/ysenarath/public-health-informatics-iscram-21.

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