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I, Theodore P Langdon, hereby submit this original work as part of the requirements for the degree of Master of Science in Information Technology-Online.

It is entitled:

Extracting Actionable Medical Data from a Twitter User's History During a Medical Emergency

Student's name: **Theodore P Langdon**

This work and its defense approved by:

Committee chair: Shane Halse, Ph.D.

Committee member: Jess Kropczynski, Ph.D.

UNIVERSITY OF Cincinnati

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Extracting Actionable Medical Data from a Twitter User's History During a Medical Emergency

A thesis submitted to the Graduate School
of the University of Cincinnati
in partial fulfillment of the requirements for the degree of

Master of Science

In the School of Information Technology
Of the College of Education, Criminal Justice, and Human Services

By

Theodore P. Langdon
MS, Criminal Justice, University of Cincinnati, Ohio, 2008
BS, Criminal Justice, Xavier University, Ohio, 1999

Committee Chair: Shane Halse, Ph.D.
Committee Member: Jess Kropczynski, Ph.D.

Abstract

As technology permeates day-to-day life, people have more and more ways to communicate. These forms of communication create a challenge for Public Safety Answering Points (PSAP). Research has shown people are posting on social media for medical help, but PSAPs do not have a way to receive these messages. This research aims to determine if using keywords and filter words can be used to find the actionable calls for help in the midst of the millions of posts made. Actionable is defined as containing enough information to determine the nature of a medical emergency and if is currently occurring or is recent enough that the poster needs help.

To determine if this was true, the most prevalent types of voice medical calls to the Cincinnati Fire Department were determined for 2021. A set of keywords and filter words was created for each call type. Then tweets were captured over a period of seventeen hours and filtered using the word lists. The filtering showed there was a valid way to find actionable tweets, and that people were posting such things. By varying the word lists, the signal-to-noise ratio can be adjusted depending on the desires of the agency. as filtering became more strict, the number of missed actionable tweets increased, while the number of incorrectly labeled as actionable decreased.

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I would like to offer thanks to my committee chair Shane Halse, Ph.D. for guiding me throughout this process and providing me with ideas on how to focus my research. I also want to thank my committee member Jess Kropczynski, PhD. for her interest in my work and for her suggestions to help guide the goals of my research. Additionally, I would like to offer a special thanks to Michael Zidar, who helped provide CAD data to aid in the creation of my search tools.

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1 Introduction

This research will focus on the concept of using technology in emergencies to help responders and those needing help communicate. Prior research (1) has shown that this can be done by using social media and can be used with little to no need for direct communication. By allowing someone to set off a request for help and then continue to do what they can to ensure their further safety, victims can lessen the chance of further injury. At the same time, responders can use tools to gain data on the situation and plan their response accordingly.

Previous incidents, such as the 2018 Hawaii false missile alert have shown that in an emergency, 911 calls can quickly overwhelm the capacity of the communications center. (2) In that case, 5000 calls rapidly came into the center, and 2500 calls were unable to connect. Even in real situations, such as an active attacker, call times to gather information takes a few minutes. When such a situation occurred at Ohio State University, the two employees working had to handle just over 3 calls a minute, with calls taking 3-4 minutes when they had usable information (3).

In 2017, Hurricane Harvey quickly overloaded the ability of traditional 911 operations (4; 5). Citizens turned to social media to call for help, but authorities tried to dissuade people from doing so. There were private groups, such as the Cajun Navy, that then took up the challenge to respond to calls for help on social media. These groups also used social media to their advantage as a way to coordinate aid and push information to the public. These events show a willingness of the public to use social media in an emergency, and that public agencies need to not only browse social media in a crisis, but they must actively search social media for calls for help.

Due to the one-to-one nature of a phone call, where a call taker can only process the call they are actively a part of, this creates a situation where higher priority calls may wait an extended period, or possibly not connect at all. When an influx of calls occurs, the call taker has their attention stretched as well (6)No matter what the severity of a call in progress might be, there is always a chance that a call waiting is of equal or higher priority. In these cases, a call taker may feel pressured to finish the current call as fast as possible to get to the next one. Thinking about the next call creates an issue in terms of situation awareness, in which telecommunicators play a role both inside and outside the emergency communications center.

Endsley's model of situation awareness (7) consists of three stages: perception of the elements in the environment, comprehension of the current situation, and projection of future status. This model is repeated from call to call throughout the day by the call taker, and their use of it helps drive the process by field units as well. The level of situation awareness a call taker has and records in the call will then be transferred to the responding unit. The responding unit will then start their own cycle of situation awareness. Overload of the telecommunicator due to excessive call volume causes a failure in all three of the stages of situation awareness. When a call taker is unable to answer all of the calls coming in, they are lacking perception of the elements in the environment. Since they are unaware of what calls are waiting, they may over or underestimate the severity of the waiting calls. This misunderstanding then causes the comprehension of the current situation to be flawed, as the call taker has built their comprehension on assumptions, rather than the actual facts. All of that means that there is no real way for the telecommunicator to take the final step of projecting future status. In the same vein, a responding unit being given flawed information will build their situation awareness incorrectly. Since the situation awareness process is cyclical, any tool that helps a user "catch up" and obtain a correct perception and begin again will help create a better comprehension and projection stage of the process.

Extracting data from Twitter creates a tool to help in these overload situations. A single "Twitter analyst" working with the incoming data is able to see multiple tweets and sort them in terms of severity, or group multiple tweets that are related to a single incident. While this data may be coming in rapidly, the analyst can "park" lower priority calls for help and allow the tool to keep gathering updates, and come back to them as time allows. This is not possible in the one-on-one situation of a phone call, where the call is no longer updated if the caller is placed on hold or the call is terminated. In an agency with multiple employees, all of the tweets can be displayed to all of the users as well, helping each employee create good situation awareness.

In traditional 911 call-taking, the call taker speaks with a victim, witness, or some other person involved in the emergency. The caller can be asked clarifying questions, to help gather and categorize the information related to the emergency. Call takers are taught to attempt to gather the 5 W's (where, what, when, who, and weapons) for each call (8). Each of these questions helps create a better picture of what has occurred, as well as what is and will occur. If a call taker is unable to get all of this information from the caller, they are expected to get, at minimum, a location. Beyond this single, critical, point each question progressively helps the call taker and responders gain a better level of situation awareness. In a routine call, the call taker will gather all of these details, if known by the caller. These questions are asked in the order of importance, where, what, when, weapons, and who. Questions such as when, weapons, and who help the call taker gauge scene safety, which may require additional resources, such as police, if there is a chance of danger.

In Emergency Medical Dispatch, there is a structured method of interrogating the caller to gather details as to the nature and severity of the incident See appendix 1). The dispatcher is given a protocol of which questions to ask and an order in which to ask them. As the interview proceeds, the answers that are given guide further questions, and instructions to the caller, or prompt the dispatcher to send resources and return to the caller for further questions. This allows for a rapid response since the caller can begin offering aid, as well as assuring the right EMS equipment is sent. Proper resource management is an important part of both critical incidents and day-to-day operations. Resource management can be reduced to three steps (9; 10):

- Identify resources - In this step, performed before any incidents, resources are categorized in the area in which they are used, such as EMS. They are also grouped by capabilities and kind, such as an advanced life support (ALS) ambulance. This allows for telecommunicators to know what a resource is capable of rapidly, as each unit is defined and the telecommunicator is aware of what this definition means in terms of response.

- Order and acquire resources - This step is often completed before an incident, with a daily line-up of units on duty. In a crisis, this may expand to calling for mutual aid from surrounding agencies or recalling off-duty staff. Situation Awareness plays a large role in this step, as future needs are projected based on past experiences.

- Mobilize resources - At this stage, the telecommunicator is sending aid to those needing help. The better the information gathered, the better the aid can be properly sent. In this step, the goal is to get the proper resource to the person needing help, but not an over-qualified resource if possible. In this way, a sudden call for a higher-level resource has a response available.

Since resources are finite, this cycle is repeated any time there is a need for a response.

Therefore, assuring low-level emergencies only receive low-level resources keeps the higher-level resources available for any higher-level emergency that arises. EMD helps agencies keep a balance of units in use and units in reserve, to be ready for a surge in calls or call severity.

Beginning in the early 2000s (11) and continuing to this day, the 911 industry has been creating Next-Generation 911 (NG911). This originally was a plan to add to the existing landline and mobile phone ties to 911, known as Enhanced 911 (E911). The original technology to be included was voice over IP (VoIP) but quickly moved into text messaging, multi-media messaging, and video chat. Social media has yet to be integrated into the NG911 platform.

There is existing research (1; 12; 13; 14), that has created solutions to gather the initial need and location of posts. The next step is to dig deeper into the user's data to see if there are preexisting conditions or other things that could warrant a modified response by emergency personnel. This will be based on the standards of Emergency Medical Dispatching, which has criteria that can alter the possible severity of the injury. Some examples are the height of a fall, whether a victim is male or female, and if a victim is an adult or child. While care would be sent in the case of any injury discovered from Twitter based on the previous research, this would allow for better resource utilization as a narrower issue could be determined.

Social media has limited ability to engage in a two-way conversation and relies on the author of a post to monitor for responses. By searching deeper into a user's posts after a post requesting help is found, agencies can better formulate an idea of what the situation is. There are existing tools that can be brought together to find this information while filtering out joking, sarcastic, or otherwise non-emergency posts. These tools can also be tailored to find the most important information as desired by the agency served, allowing for integration into existing protocols. Once a person's post has been identified to be calling for help, there needs to be a way to mine their history for these important ideas. Because Twitter uses screen names and often no geotags, there is a possibility of delay in response as that information is gathered.

Using open-source tools such as Tweepy (15) to mine Twitter for keywords will create a pool of tweets, however, this data will include actual calls for help along with people who might be joking or exaggerating. By using the application Pandas (16) coupled with Natural Language Processing (17), this data can be weighted and given a sentiment score to help filter the most pressing needs to the top of the priority list. Natural Language Processing will search deeper into the tweet, using the logic of the English language to determine if the poster is actually in need of help. Additionally, the NLP software can be taught location names and local colloquialisms about the area to help identify a dispatchable location. Tweepy can then be re-applied to the data gathered to search the tweet history of the user of individual tweets to be collected and processed to gather past medical information or changes in the need for aid.

2 Literature Review

2.1 The history and application of Emergency Medical Dispatch

Emergency Medical Dispatching protocols began as a concept in the 1970s (18). The initial goals of the system were to both offer the proper pre-arrival instructions to the caller, as well as reduce abuse of the EMS/911 system. Early in the development, the idea of sending the proper level of response was also incorporated into the systems. A set of protocols, first adopted in Utah in 1983, was then adopted as a recommendation by the US Department of Transportation. In the 1990s, EMD solidified into a standards-based system that requires formal training and continuing education.

The American Society for Testing and Materials (ASTM) has defined the minimum standards for the training of Emergency Medical Dispatchers (19). Within this standard, the key component of the system is the emergency medical dispatch priority reference system (EMDPRS), which must be approved by a medical director (20), and contains the following:

- Systematized caller interrogation questions - These questions are chosen to gather the important details in the shortest amount of time. They are scripted, and often expected to be asked in a prescribed order. Questions are often closed-ended, to prevent the caller from giving information that is not needed.
- Systematized pre-arrival instructions - The medical director, along with other EMS experts creates a set of instructions that allows callers to help the person hurt, or

even themselves. These instructions may be medical in nature, such as applying firm pressure to a bleeding area. They may also be a way to aid EMS, such as telling a caller to put pets away, turn on the porch lights, and unlock the doors. These instructions may be given during the interrogation in severe cases such as a stroke, but are often given after the EMS unit has been dispatched and the caller is awaiting their arrival.

- Protocols matching the dispatcher's evaluation of injury or illness severity with vehicle response mode and configuration - The responding agency sets guidelines as to what and how many personnel and equipment are sent to a call for service. Through the questions asked a severity is determined by the EMD system, and the units that are dictated in the guidelines are sent.

Additionally, ASTM (21)has defined the key tasks of an Emergency Medical Dispatcher as:

- Receive and Process Calls for Assistance - Depending on the system used, processing may entail using a software program to complete the caller interrogation, or may rely on paper guidelines.
- Dispatch and Coordinate Appropriate, Available Response Resources - By using resource management techniques and protocols, telecommunicators assure the caller receives the proper help in their situation. At the same time, the telecommunicator is keeping track of where all the agency's resources are located, and what status they are in.
- Provide Information and Pre-arrival Instructions - This standard expands upon the pre-arrival instructions to add keeping the caller informed of what is happening. EMD systems often have points in the process where the telecommunicator will advise a caller that EMS is on the way, or that the call has been sent to be dispatched.

These standards both require the use of pre-arrival instructions, exactly as written and approved by a supervising physician. Research has also shown (22) that 88.7 percent of citizens expect that there will be some sort of pre-arrival instructions given. This creates an issue when using a one-way communication method, such as Twitter. Protocols have already been modified in such a way that they can still be used with a caller unwilling to render any sort of aid or a caller hangs up (23), which would be applied to Twitter and other social media.

One of the leading organizations for Emergency Medical Dispatch has researched the idea of risk management within the field of emergency communications (24). The primary objective of this study was to characterize the most common types of adverse events, actions, and omissions of action that lead to lawsuits against emergency dispatchers and their agencies. The data was obtained via publicly available records, including legal documents from local, state, and federal case files, and documents related to dispatch litigation obtained from research and news databases. 84 dispatch-related legal cases were reviewed, of which five were excluded for various reasons. Multiple (two or more) calls was the most common dispatch problem named as the issue in the suit, followed by delayed dispatch or response, customer service issues or mishandled calls, and failure to provide pre-arrival / post-dispatch instructions. The findings indicate that there exists a clear, expected, and enforceable standard of practice for emergency dispatching and that this standard is increasingly applied by both the courts and the public in judging the actions of emergency communications centers and individual dispatchers. As more and more agencies are adopting tools to search social media or accept more forms of communication beyond standard voice telephone, reducing liability will be a challenge. Since a key part of risk management is identifying threats, agencies will need every tool they can at their disposal to know what threats exist. Using Twitter with the idea of one-way communication, as they are set already for hang-ups or refusals allows agencies to help people who might otherwise not be able to ask for help.

2.2 Identifying the need for emergency response

Twitter users generate thousands of tweets per second, which creates a large pool of data for researchers or responders to sift through. Trending topics and event detection and tracking are both useful in emergencies to help responders best allocate resources. Obtaining situational awareness of any event is crucial in various application domains such as natural calamities, man-made disasters, and emergency responses. Researchers have focused on the users' emotions, concerns, and feelings expressed in tweets during emergencies, and analyzed those feelings and perceptions in the community involved during the events to provide appropriate feedback to emergency responders and local authorities(25). Researchers analyzed the tweets from the Las Vegas Music Festival shooting (Oct. 2017) and noted that the changes in the polarity of the sentiments and articulation of the emotional expressions, if captured successfully can be employed as an informative tool for providing feedback to EMS. This kind of feedback can alert responders to situations that are escalating or may require more than an EMS response, such as a need for police or hazardous materials unit.

Most social media research is limited in scope to the United States. In a paper, German tweets of the 2013 European Flood were captured and analyzed using descriptive statistics, qualitative data coding, and computational algorithms (26). The authors' work illustrated that this event provided sufficient German traffic and geo-locations as well as enough original data (not derivative). However, an up-to-date Named Entity Recognizer (NER) with a German classifier could not recognize German rivers and highways satisfactorily. This raises a concern for locations with a local name that is not official, or non-English speakers tweeting in a disaster. Slang, "text speak", and other idioms may raise the same issues. The authors of this study revealed linguistic barriers resulting from irony, wordplay, and ambiguity, as well as in retweet behavior. To ease the analysis of data they suggest a retweet ratio, which is illustrated to be higher with important tweets and may help in selecting tweets for mining. This method can also be used to help narrow down reports as duplicates since a retweet is already identified by the original sender.

During Hurricane Harvey, social media was seen as a "savior"(27). As people posted messages asking for help, groups of citizens banded together to assist. These postings, both asking for help and for offering aid, were being posted due to the inability of the local authorities to keep up with voice calls (28). Call volume to 911 spiked to 75,000 over the weekend of the hurricane, where a normal weekend would have an average call volume of 27,000. Even though the authorities asked citizens to refrain from using Twitter and other social media systems, people continued to do so. As people posted their needs, other people were offering help as they could. While this method worked out in this case, a coordinated effort from the local authorities could help prioritize and schedule responders in a way to prevent gaps in help. Additionally, this research shows that even when specifically directed not to, people's first response to an overwhelmed 911 system was to turn to social media. This shows how important monitoring social media has become for agencies, as the public's expectation is someone is doing so.

Figure 2.1:
An example of tweets from the Houston PD asking people to not post on Twitter (left) and an example of a tweet asking for help. Note the message being addressed to the governmental agencies as well as the media.

2.3 Availability of Twitter Data

When selecting a social media platform for this research, availability and openness were key criteria. Twitter promotes the use of their API v2 for research, with one promoted use case being a way to better their platform for all users (29). Twitter's academic licensing allows more complex operations when searching for tweets to be retrieved, which will allow for an ample sample of data without exceeding any data caps or limitations of the licenses.

Twitter also marks retweets so non-original messages can be discarded instead of creating duplicate data. The text limitation of 280 characters helps authors focus their language as well since any superfluous words will cause them to exceed the character counts. The use of hashtags or embedded user references by so many users can be used as a way to quickly filter as well. During Hurricane Harvey (30) tweets often contained a hashtag or reference to the Hurricane or a rescue agency in Houston.

Smartphones and social media such as Twitter are creating a world where everyone is both consuming and creating large amounts of data. At the scene of an emergency, onlookers, victims, and first responders all are able to share images, videos, and text details of the emergency. With such a large volume of data being created continuously, someone trying to find true emergencies, and once located, pertinent information becomes a challenge. An event with multiple victims exacerbates the problem even further. The researchers in this paper (31) investigated a sample data set of tweets that were collected during a storm event passing over a specific area. The sample was manually labeled by three emergency management experts who annotated the sample data set to obtain valid information through the identification of the event-related tweets. Event-related tweets were then used to extract the common patterns and to define event-related terms based on term frequency analysis. The terms were used to evaluate the event-relatedness of a sample data set through a relationship scoring process. Then, each sample tweet is given an event-relatedness score which creates a score of how related a tweet is to the storm event. The results were compared with the ground truth to determine the cut-off relatedness score and to evaluate the performance of the method. The results of the evaluation indicated that their proposed method was able to detect event-related tweets with about 87 percent accuracy in a timely manner.

3 Research Statement

3.1 Research Question

With the increase in non-voice communications overall, I wanted to investigate if there were ways these forms of communication were being used for calls for medical help and if there was a way to extract and use this information. The Emergency Medical Dispatch protocol requires call takers to enter the answers in the same language the caller uses. This creates a record of a conversation rather than pre-determined categories or counts. Using this historical data from voice calls leads to the first research question:

To further use the data captured, it would have to be presented in or converted in a way that could be presented to a telecommunicator to act upon. There are multiple Computer Aided Dispatch systems in use around the world, using different methods for processing data. This fact led to the second question of this research:

> **Can data important in guiding emergency response be extracted from tweets determined to be calls for medical help and presented in a usable format for emergency telecommunicators?**

3.2 Aims

3.2.1 Collecting initial data

Computer-Aided Dispatch systems record details on each call for service, and offer a good source for finding the frequency and needs in calls for service. By obtaining a one year collection of medical calls, the most often used call types can be measured. These most frequent calls would then be examined for words that are repeated in multiple calls and a list of keywords will be created. Once the keyword list is made, a secondary list of filter words will be created for word pairs and phrases to help further refine the searches to be applied to the Twitter data obtained.

3.2.2 Categorizing the request

The initial stage of this step will be to review protocols to find what information needs to be found in a tweet to decide that a poster is in need of help. The Association of Public-Safety Communications Officials (APCO) is an industry organization that sets standards for call processing within the field of emergency communications. Within their standards, they divide medical emergencies into two types - Basic Life Support (BLS) and Advanced Life Support (ALS)(8). By using guide cards[Appendix A], a telecommunicator can determine which level of care is needed. The guide cards focus on critical questions first, which will be the criteria used to interpret the data from Twitter. The information sought will be if the person is breathing, are they bleeding, and are they conscious. The answers to these questions will create enough situation awareness to determine the level of response needed.

3.2.3 Output to the telecommunicator

The data gathered will need to be presented to the telecommunicator in an easy-to-read, and standardized format. The National Emergency Number Association (NENA) sets industry standards for technology within the emergency communications field. While there is no standard in place for dealing with social media posts, there are two that apply to the presentation of data.

The first, *Recommended Generic Standards for E9-1-1 PSAP Intelligent Workstations* (32), is a standard that aims to put as many systems together on one computer for the telecommunicator to use without having to reach for a KVM switch or a separate mouse and keyboard. Within that standard, one requirement is that of a messaging feature. Specifically, it "..allows the broadcast of a visual message to each workstation or a select group of workstations in the PSAP without interrupting the call-taker activity". This feature often works similar to an email client and would be a good way to present the data pulled from Twitter to a call taker so that it is seen, but can be set aside and returned to as needed as the call taker works through the incident.

The second NENA standard that guides a method to display this information is *NENA Standard for Emergency Incident Data Object (EIDO)* (33). This document creates a vendor-neutral, universal set of data elements that need to be present for data to be sent directly into the Computer Aided Dispatch system. This standard also includes a list of common incident types that will be used to classify the nature of the medical need.

By using both of the standards as a basis for sending the data from Twitter to CAD, the agency receiving the call for service can then manipulate the data in a way that suits their needs. As long as the CAD system is compliant with the EIDO standard, the incident can be tracked from start to finish using this output or can be sent to another agency as a single package via networks between PSAPs.

4 Methods

4.1 Determining keywords and filter words

To create a list of the most common words used when a poster is in need of medical aid, a data set of all calls for service for the Cincinnati Fire Department was downloaded from the "Cincy Insights" data portal (34). The site was created by the City of Cincinnati to share data from many sources, across city departments. For this research, the data used was from the Cincinnati Emergency Communications Center's Tri-Tech computer-aided dispatch system. Options are present in the portal to extract data with filters, but I downloaded the full data file so no calls would be missing. This file contained all of the CFS to Cincinnati Fire/EMS from January 2015 to the date downloaded. I extracted the data for CFS in 2021, which totaled 104,961. The Cincinnati Fire Department's Computer Aided Dispatch system categorizes data into 100 incident types, of which 56 are medical in nature. The EMD system used only contains 32 categories, but the department has split some call types.

The rows that contained these 56 incident types were then extracted using Microsoft Excel. I compared the prevalence of call types in the way that CFD separated them to retain their classifications. Using a pivot table, the total count for each incident type for the year 2021 was calculated. The top four categories were:

The incident type of Sick Person was discarded due to two factors. The first is that under the protocols used by the Cincinnati Fire Department, there are non-emergency and emergency calls that would fall into this category, such as needing a ring cut off, or a person

Sick Person	10740
Breathing Problems	8338
Falls	7660
Chest Pain / Chest Discomfort (Non-Traumatic)	4676

Table 4.1: Top four call types in 2021.

reporting they are constipated. For this reason, the 10,740 calls coded under this run type are not all emergencies. While the department has split off some types, such as heroin overdose being separated from a drug overdose, there are calls that do not fit a category exactly. In those cases, the call-taker will choose the call type of sick person and add detailed notes as to the nature of the call. This creates a situation where the sick person call type becomes a "catch-all" for calls that do not neatly fit into other categories.

The second factor is the Covid-19 pandemic, which officially started on March 11, 2021 (35). From 2020 to 2021 the Cincinnati Fire Department went from 6686 sick person calls to 10740. This 60.63% increase was higher than the increases of the other call types for the same years. Research has shown that during a crisis, people often develop psychogenic symptoms. A well-known example of this was observed after the Aum Shinrikyo Sarin attacks in Tokyo. After these attacks, 81% of those presenting at medical facilities had no physical symptoms, and many had not been exposed to the chemicals used (36). These patients, often referred to as the "walking well", cause an increase in calls for service, but upon medical examination are released. Covid-19 symptoms that were psychogenic would fall under the sick person category since they would not be causing physical issues.

Call Type	**2020**	**2021**	**Increase**
Sick Person	6686	10750	60.63%
Breathing Problems	5612	8338	48.57%
Falls	5163	7660	48.36%
Chest Pain / Chest Discomfort (Non-traumatic)	3341	4676	39.96%

Table 4.2: Comparison of call volume from 2020 to 2021.

The full data record for each call for the remaining three call types was then obtained from the CAD database, for all calls in 2021. This record included a column for comments, which includes any notes added to the run by the call taker. Within that column, there is a line that is prefaced with "[ProQA: Case Entry Complete]" which is a system message that is placed before the notes the call taker enters after asking the question "tell me exactly what happened". Since these notes are expected to be entered as the caller answers, this would be in a tone and manner closest to a tweet. This column then had all ages, sexes, and races removed as well as the NLTK Toolkit stop words (37), using a pandas function that searches for text in a string to allow for a word frequency count.

The remaining parts of the comments then had individual words counted using the pandas Series.str.count function. Once that list was completed, it was filtered to find the prevalence of medical terms using the EM Terms (38), the CrisisLex Lexicon (39), and the Twitter Health Keywords(40) lists. The medical terms were then used to create a list of keywords and filter words to compare against tweets. Keywords were chosen by their similarity to the selected three call types; breathing, heart, and falls. Once the keywords were selected, the remaining terms that appeared were matched to keywords by searching for word pairs that appeared in the EM Terms and CrisisLex lists. Some filter words were found with multiple keywords, and these were placed into another group that I named "multi-issue" for clarity.

As an example, to create a list of a keyword and filter words determined for breathing issues, I looked for the words related to the main complaint of the caller, compared to the incident type. Breathing was the second most frequent word in the text, and ties directly to the complaint of breathing problems. Then, to make the search tool search widely, the word is reduced to its root word. Breathing becomes breath to capture all variations of the word (breathing, breaths, etc), as well as misspellings. Then, once a keyword was chosen, phrases and word pairs containing that keyword were collected from EM Terms and CrisisLex.

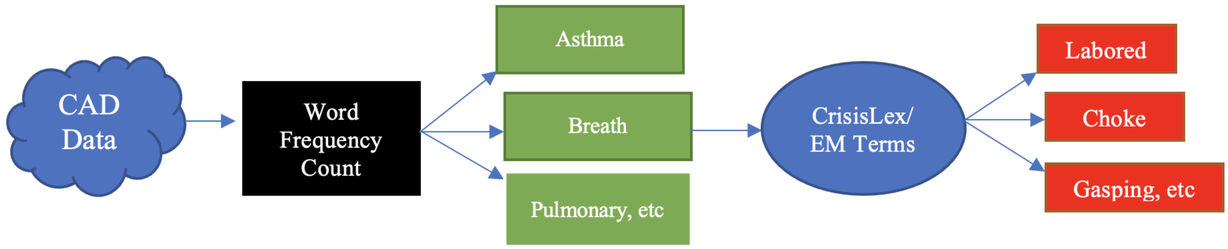

Figure 2. The flow of how keywords and filter words were chosen.

In this example, the Keywords are selected at stage 3 (green). Once chosen, the filter words are selected using the groupings in EM Terms and CrisisLex. As the pair words/phrases are checked to see which contain the keyword, filter words are chosen (red).

Within the data from Cincinnati Fire/EMS calls, 5132 calls used these words, so only 61.55% of the calls for trouble breathing contain a word with a base of breath. The process was then repeated for the next most frequent word used in these calls until all of the calls had a keyword assigned. Filter words were sometimes present for multiple keywords, images representing the groupings can be found in Appendix 2.

Additionally, as the word pairs were being compared, it was found that often the same pairs came up using the terms "fall", "slip" and "trip" interchangeably. For this grouping, I added a second set of keywords to restrict any matches to falls that resulted in an injury of some sort (see appendix 2, Figure C). In this case, a word such as "bruise" or "break" would also need to be in the text before applying a filter word search.

4.2 Gathering Tweets

To gather the tweets, I used a Java application provided by my advisor that collected live Twitter data based on keywords appearing in the text. This tool was created using the twitter4j library (41). I used the keywords from the four sets to collect tweets from April 8th, 2022 at 1450 to April 9th, 2022 at 0740. This resulted in 1,110,237 tweets that contained at least one keyword. Based on estimates (42) of tweets per hour, approximately 353,500,000 tweets overall would have been posted in that same period. The tweets with keyword matches account for 0.31% of postings based on this estimate.

4.3 Selecting Tweets from those gathered

4.3.1 Sorting tweets by keyword

To filter a sample of the raw Twitter data, 1000 tweets are chosen randomly. The script then checks the text of the tweet for keywords, and if found keeps that line. In the last step, the matching tweets are exported as a CSV file.

```
REQUIRE Keyword List
REQUIRE AllTweets.csv
SELECT 1000 random lines    THEN
     add lines to <dataframe>
  THEN
     WRITE <dataframe> to 1000Tweet.csv
```

```
READ 1000Tweet.csv
IF line contains <keyword> in text column of 1000Tweet.csv
  THEN
     add lines to <dataframe>
  ELSE
     END
WRITE <dataframe> to output.csv
```

4.3.2 Removing duplicates and cleaning the data

To remove the duplicates, a process is run that finds duplicate lines and then drops all but one of the posts. The method to eliminate the retweets (RT) and username mentions (@) drops any lines with this text This process was run on the raw data file to create a cleaned data file used for the remainder of the research.

```
  REQUIRE AllTweets.csv
IF line contains "@" or "RT" in the text column of AllTweets.csv
  THEN
    drop line
IF line A = any other line
  THEN
    drop all lines except line A
SELECT 1000 random lines
  THEN
    add lines to <dataframe>
  THEN
    WRITE <dataframe> to Cleaned1000.csv
```

4.3.3 Sorting tweets by keyword after cleaning

The script loads the 1000 random texts from the cleaned data. Following that, the script checks the text of the tweet for keywords, and if found keeps that line. Finally, the matching tweets are exported as a CSV file.

```
REQUIRE Cleaned1000.csv
REQUIRE Keyword List
  IF line contains <keyword> in "text" column of Cleaned1000.csv
    THEN
      add lines to <dataframe>
  ELSE
END
WRITE <dataframe> to <output.csv>
```

4.3.4 Sorting tweets by keyword and filter words after cleaning

As in the keyword search of cleaned data, the script selects the lines matching keywords. Rather than exporting these lines, they are held in a data frame, where a second search is performed, matching the filter words to the tweets that were found to have keywords. After the second search, the lines remaining are exported as a CSV file.

```
REQUIRE Cleaned1000.csv
  THEN
    add lines to <dataframe>
THEN
  IF line contains <keyword> and <filterword> in "text" column
of <dataframe>
  THEN
    add lines to <dataframe2>
ELSE
  END
WRITE <dataframe2> to <output.csv>
```

4.3.5 Converting selected tweets to EIDO for PSAP action

By retaining certain columns in the CSV of tweets detected as actionable, and adding required data columns and data, a complete Emergency Incident Data Object could be created. The EIDO standard contains 1186 data components but only requires 22 as a minimum. These required data components are focused mainly on the 5 W's (who, what, where, when, why) of emergency call taking. From the Twitter data, the when and what of an incident can be determined and retained. Additionally, a unique tracking number is easily copied from the tweet ID, which can also be used if the tweet needs to be found using a different tool at a later time. The additional data components are important to a receiving agency to show that the data came from Twitter, and what was done with the information before, during, and after an incident. It also tracks who has made notes or changes and the role they hold.

I created a hypothetical service for these tweets of "medical.twitter.com" since there is no official service at this time. The analyst looking at the data would also be tracked as a call taker from a partner agency of the PSAP. Additionally, the standard currently would classify Tweets as a medical alarm and the analyst as an involved party

All of the data was added using pandas, and other than the Tweet ID, creation time, and text, were a set string of data or blank. This data would be added to, as well as data components inserted, as needed by the receiving system. . In a real-world application, this minimum data is required for the EIDO to be accepted by a CAD system.

After the elements were added, the resulting CSV was converted to a JSON file that complies with the EIDO standard using pandas. For this research, the 89 calls for service were left as one file to be imported to the receiving CAD system. If needed due to limitations of a system loading the data, the file could be split into 89 separate JSON objects.

Data Component Name	**Explanation**	**Data used and source**
$ref	Renaming of the "tweet ID" column to meet EIDO tracking standards	Tweet ID number is carried over from the initial Twitter data
callStartTimestamp	Renaming of the "message date" column	The creation time of the tweet from the initial Twitter data
notesComponent	Renaming of the "text" column. This is the column that explains the call type	Text from the initial Twitter data
notesActionComments	Updates and notes added to the incident as it progresses or is closed	This is a required component but is only filled with updates after the initial incident is read. It is set to blank.
eidoVersion	This component is currently always "1.0" as there is only one version of the standard to date	1
issuingElementIdentification	The agency or service responsible for the creation of the data	medical.twitter.com a hypothetical identifier assigned to Twitter for interfacing
agencyComponent	All agencies involved in the incident	twitter.com – additional agencies would be added to this as the incident progressed
agentRoleRegistryText	The role of the agent	Call Taking– this is the role as detailed in the EIDO standard for the originator of an incident
agencyReference	Identifies the agency employing or contracting with the agent	twitter.com – while this data would be created without a person intervening, the standard requires an "employer"
agencyRoleDescriptionRegistryText	The role of the agency involvement in the incident	Assisting – this is the role as detailed in the EIDO standard for an agency that provides information but does not directly assist in the response
incidentTrackingIdentifier	A tracking number created by the receiving system to identify any incidents that are merged or split from the initial incident	Blank – this number is created by the receiving system as needed
linkDirectionCode	What relation the EIDO is to an incident	Parent – since this data is being sent to a response agency system, it will always be a parent incident
incidentTypeCommonRegistryText	The initially determined type of incident based on the EIDO standard list	ALRMED (Medical Alarm) – This is the closest incident type to the data twitter provides. Agencies would then convert the information into a type that matches their protocols, or leave it as an alarm

Table 4.3: Data Components required by EIDO Standards

Data Component Name	Explanation	Data used and source
standardPrimaryCallType	The type of call based on NENA standards	Intervene – based on the NENA i3 standard this data would be a request for intervention by the receiving agency
direction	The direction the EIDO data is traveling	Internal – By NENA standards, this is the direction when the creator and recipient are in the EIDO sender. While the data is from Twitter, the extraction and conversion would theoretically be within the agency.
callStateRegistryText	The status of the call when the EIDO was created	callBegin – this shows the EIDO is the initial action in the call
deviceContactHeader	Information that enables agents and responders to possibly reach (call back) the device that initiated the call.	"twitter.com – no way to call back" – Since the data on Twitter is primarily one way, there is no way to "call back"
updatedCbnIdentifierUri	This data element (in the form of a URI) is used to track additional telephone numbers or SIP equivalents that can be used to contact the reporting party of the parent call.	Blank – This element is required, but since there is no voice system involved, it is blank
dispositionCommonRegistryCode	A code assigned to the incident when an agency passes the incident to another agency or closes the call to note what was done by the agent	15- this is the NENA standard that means "Referred to partner agency/Animal Control/Medics/Fire, etc". While the data is being referred internally there is no code that corresponds to an internal transfer.
dispositionDescriptionText	This is a text field that describes the disposition of the EIDO currently. It is free text to match agency dispositions as needed.	"Sent from analyst to CAD for processing" – This clarifies that the code 15 was an internal referral when viewed
notesActionComments	Notes created by an agent entered in HTML fragments	Blank – this is a required field, but would not have any information at this stage in processing
personIncidentRoleRegistryText	The relation of the initiator of the call to the patient/victim	Involved person – by NENA standards, this is used for unknown relations. It is used because there is no standard term for an outside analyst

Table 4.4: Data Components required by EIDO Standards (cont.)

4.4 Assumptions on Location Data

There are multiple data components present in the standard that apply to a call location. The precision of these components varies from a specific GPS location to a general area within a plain text field. However, this research did not attempt to extract location data from Twitter. As other researchers create tools to gather this data, they could be incorporated into this method.

5 Results

5.1 Iteration 1 – Establishing a Baseline

For the baseline, there was no other filtering applied to the data prior to the selection of the random sample. Once that sample was selected, I ran a keyword search using pandas. The results showed that 449 (98.5%) of the tweets were incorrectly flagged as actionable, and only 7 (1.54%) were correctly selected. Within 449 incorrectly selected, there were many retweets (357) and direct username mentions (79). These retweets and username mentions were manually checked, and none had any request for help or medical duress. Had a retweet contained such a request, the actionability would be limited due to the separation of the tweet from the original poster. Direct username mentions, however, could be beneficial in allowing a user to direct the tweet toward a public entity's official Twitter feed in the future.

	Detected as Actionable	Not Detected As Actionable
Actionable	7	0
Not Actionable	449 (includes 357 retweets)	544 (includes 89 duplicates)

Table 5.1: Baseline Signal Detection

Using only a keyword search gives a high amount (98.5%) of non-actionable tweets for a user to sort through to find the few that are actionable (1.54%). This creates a situation where the bulk of the time dedicated to going through tweets would be used to eliminate noise. While no actionable tweets were omitted, a user would be slowed by the number of incorrectly labeled as actionable tweets presented.

5.2 Iteration 2 – Permissive filtering

Using pandas, tweets starting with "@" or RT were removed from the full file of tweets. Additionally, the file was cleaned of any possible duplicates. This resulted in a file of 204,178 unique tweets. Then the data was queried by pandas and NumPy to gather 1000 random tweets using the same script as used in the baseline. The tweets were then queried to collect any that contained the keywords as described in the Methods section. This resulted in a larger number of tweets detected as actionable, as well as a higher percentage (7.2%) correctly detected with actionable data.

	Detected as Actionable	Not Detected As Actionable
Actionable	44	0
Not Actionable	565	391

Table 5.2: Permissive Filtering Signal Detection

This method lowered the percentage of incorrectly labeled tweets (92.7%), but this still leaves a large ratio of signal to noise.

5.3 Iteration 3 – Restrictive filtering

This iteration used the same data as the Permissive attempt, but checked against keywords in the first pass, and then by filter words in the second pass.

Adding a filter word search to the keyword resulted in a much higher percentage of the tweets being detected as actionable correctly (27%), The restrictive approach did show a drawback, where 20 actionable tweets were incorrectly labeled as not actionable. While these were missed, the user would be able to quickly process the tweets detected as actionable with the 88.5% reduction in incorrectly identified tweets. The filter words also correctly eliminated 89.1% of the data was not actionable.

	Detected as Actionable	Not Detected As Actionable
Actionable	24	20
Not Actionable	66	891

Table 5.3: Restrictive Filtering Signal Detection

5.4 Summary

While using keywords alone does not leave any actionable tweets out, there is a large amount of noise remaining that hinders the effective gathering of data. As the parameters for searching were made stricter, the signal-to-noise ratio was reduced. The strictest, keyword and filter words, has a small signal-to-noise ratio. This comes at the expense of the 20 tweets that were missed and incorrectly identified as not actionable. Further refining of the filter words could work towards a reduction in the tweets missed with an amount of noise that is still acceptable.

6 Findings

6.1 Discussion

Using available data to find the most common calls for service allowed me to focus on three categories. This data then could be used to get the full-text records for these categories, from public record CAD data. Using word frequency counts and phrases where these words appear created, a set of keywords and filter words that can be used to sort tweets. The iterations of combinations of keywords and filter words revealed that as the noise was reduced, the chance of omitting valid tweets rose. The data gathered was found to be enough to use as the base of an EIDO, when required identifiers were added.

The fact that tweets already are being posted containing apparent calls for help was an area that I wanted to measure during a non-disaster period. Historically, agencies have asked for people to not use social media to do so, claiming it will overwhelm their call takers, regardless of disasters or not. Those same agencies may or may not look at Twitter regularly. This creates a situation where 0% of the tweets requesting help get a response.

The use of keywords and filter words in this research shows that there is a way to create a tool to help discard non-related tweets and act on those related. An agency adopting this type of system could choose to use one or both of the methods above the baseline attempted in the research to balance their risk of missing or delaying a response to a tweet. If an agency chooses to operate with just the keyword method, they would expect to miss very few tweets but have to accept that it may take longer to process them. An agency that used keywords and restrictive filter words would know they can quickly process, but at the cost of missing tweets. The tool can also be tightened or loosened as needed during a spike in activity. Such a tiered or sliding set of words can be applied based on policy to fit the needs of the situation.

Using available CAD data allowed for a way to find the most frequent language used in standard voice calls for service. By using this method to create a keyword and filter word list, agencies can update the lists as frequently as they choose. Seasonal trends or epidemics could be incorporated quickly to help find more calls for help. As the need for faster processing rises because of call volume, the sorting could be made stricter. Word lists can also be updated as slang changes or to add vernacular for a specific area. Another benefit to this method is allowing agencies to choose what types of incidents they would consider a response to. With this kind of choice available, an agency could only look for advanced life support level calls, or look for anything medical.

The data shows that Twitter users are posting comments that may be calls for medical aid. While they are a small percentage of overall tweets, using the methods of research can provide a tool to sort quickly through the millions of tweets posted every day. Agencies can also tighten or relax the filter words to modify the signal-to-noise ratio as the situation dictates. In a disaster, an agency would likely tighten the filter so the person analyzing them could respond and refer them faster. At a more routine time, the same agency can loosen the filter to assure they are getting all of the calls for help, but at a slower pace due to the number of false positives.

6.2 Implications

Localization for Vernacular

While looking at the results, there were two found to be correctly labeled as a request for medical help but were placed under the wrong keyword. The term "fell out" caused the text to be placed under the fall category. Reading the full text, it actually referred to a person passing out, not a fall. The end result would be the same in this case, the dispatch of a medical unit, but it points to the importance of assuring the system is set up for the area it is being utilized in.

6.2.1 Risk Aversion

When comparing the permissive and the restrictive filtering iterations, the concept of risk aversion must be taken into consideration. An agency has the ability to expand or shrink the risk of missing a tweet with how strictly the filters are applied. Additionally, this method allows an agency to create multiple sets of word lists to apply depending on the volume of calls for service. During normal operation, the agency could allow for a more permissive filter, knowing there is time to allow them to do further processing. Then during a crisis, the system could be switched to a more restrictive filter, so the Tweets presented need little to no further processing.

6.2.2 Processing by a Human

Regardless of what level of filtering is used, the Tweets found will require human interaction before being dispatched. This can be done prior to the call for service being sent to the dispatcher by an analyst, or by the dispatcher upon receiving the EIDO. At this step, the person looking at the data will need to make decisions related to department policy as well as assuring the incident is not a duplicate. In the case of a duplicate, the information from the Tweet can be merged or flagged by the CAD system to help increase the Situation Awareness.

7 Future works

During this research, I found that keyword and filter words created an acceptable amount of correctly categorized tweets in the chosen call types without the need for Natural Language Processing. However, since call types are ultimately controlled by the agency's medical director(20), agencies can have varying numbers of problem types, as well as sub-types and modifiers to further denote the nature of the call. Because of this, only having keyword lists could become a cycle of updating every time an update occurs. Using NLP would help extract the more nuanced calls for service and help sort them into the right category. Additionally, NLP could reduce the need to use root words and catch more misspelled words, for less effort in setting up a system. NLP could be trained to keep up with slang as well, so a tweet not made using perfect English could be processed.

NENA's standards are reviewed constantly, which creates an opportunity to add the ideas from this research to the next version. To do so, the experiment would have to be tried at multiple PSAPs and on multiple CAD systems to measure the accuracy. I was unable to gain access to a CAD system that is configured to accept EIDOs during my research. Such a system would be an important tool for the next step of assuring this data is received and processed correctly. At the same time, users could be recruited to process the calls imported, to see if it meets their needs.

REFERENCES

[1] J. Kropczynski, R. Grace, J. Coche, S. Halse, E. Obeysekare, A. Montarnal, F. Bénaben, and A. Tapia, "Identifying actionable information on social media for emergency dispatch," in *Proceedings of ISCRAM Asia Pacific 2018: Innovating for Resilience – 1st International Conference on Information Systems for Crisis Response and Management Asia Pacific.*, K. Stock and D. Bunker, Eds. Massey Univeristy, pp. 428–438, journal Abbreviation: Iscram Ap 2018. [Online]. Available: http://idl.iscram.org/files/jesskropczynski/2018/1672_JessKropczynski_etal2018.pdf

[2] D. Nakaso, "Honolulu's 911 system overwhelmed during panic," journal Abbreviation: Honolulu Star-Advertiser Publication Title: Honolulu Star-Advertiser. [Online]. Available: https://search.ebscohost.com/login.aspx?direct=true&db=pwh&AN=2W6120036404&site=ehost-live&scope=site

[3] Ohio State University Department of Public Safety Division of Emergency Management, "After action review active aggressor attack november 28, 2016: Summary of incident details, lessons learned & corrective actions."

[4] W. R. Smith, B. W. Robertson, D. Murthy, K. K. Stephens, and J. Li, "Social media in citizen-led disaster response: Rescuer roles, coordination challenges, and untapped potential," p. 11.

[5] When 911 failed them, desperate harvey victims turned to social media for help. Section: Weather. [Online]. Available: https://www.dallasnews.com/news/weather/2017/08/27/when-911-failed-them-desperate-harvey-victims-turned-to-social-media-for-help/

[6] National Emergency Number Association (NENA), PSAP Logistics Committee, Task Overload, and Working Group, "NENA PSAP task overload management information document." [Online]. Available: https://cdn.ymaws.com/www.nena.org/resource/resmgr/standards/nena-inf-037_task_overload_m.pdf

[7] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," vol. 37, no. 1, pp. 32–, 32. [Online]. Available: http://link.gale.com/apps/doc/A17244832/EAIM?sid=bookmark-EAIM&xid=f2698af0

[8] APCO Institute, *Public Safety Telecommunicator 1*, 7th ed. APCO International.

[9] Federal Emergency Managment Agency, *IS-0703.b NIMS Resource Management - Student Manual*.

[10] ——, "National incident management system: Third edition." [Online]. Available: https://www.fema.gov/sites/default/files/2020-07/fema_nims_doctrine-2017.pdf

[11] G. Bischoff, "NENA wants coordinated NG911 effort," vol. 23, no. 12, p. 12, place: Littleton Publisher: Informa. [Online]. Available: https://uc.idm.oclc.org/login?qurl=https%3A%2F%2Fwww.proquest.com%2Ftrade-journals%2Fnena-wants-coordinated-ng911-effort%2Fdocview%2F197251017%2Fse-2%3Faccountid%3D2909

[12] T. Simon, A. Goldberg, L. Aharonson-Daniel, D. Leykin, and B. Adini, "Twitter in the cross fire—the use of social media in the westgate mall terror attack in kenya," vol. 9, no. 8, p. e104136. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4143241/

[13] R. Grace, J. Kropczynski, S. Pezanowski, S. Halse, P. Umar, and A. Tapia, "Enhancing emergency communication with social media: Identifying hyperlocal social media users and information sources," vol. 10, no. 3, pp. 20–41, publisher:

IGI Global. [Online]. Available: https://www-igi-global-com.uc.idm.oclc.org/gateway/article/www.igi-global.com/gateway/article/227725

[14] R. Grace, S. Halse, J. Kropczynski, A. Tapia, and F. Fonseca, "Integrating social media in emergency dispatch via distributed sensemaking," in *Proceedings of the 16th International Conference on Information Systems for Crisis Response And Management*, Z. Franco, J. J. González, and J. H. Canós, Eds. Iscram, ISSN: 2411-3387 Journal Abbreviation: Iscram 2019. [Online]. Available: http://idl.iscram.org/files/robgrace/2019/1897_RobGrace_etal2019.pdf

[15] Tweepy documentation — tweepy 4.4.0 documentation. [Online]. Available: https://docs.tweepy.org/en/stable/index.html

[16] User guide — pandas 1.3.5 documentation. [Online]. Available: https://pandas.pydata.org/docs/user_guide/index.html

[17] E. S. Antar, Mohamad (Moe), "twitter-nlp-toolkit: Tools for collecting , processing and analyzing twitter data." [Online]. Available: https://github.com/eschibli/twitter-toolbox

[18] B. S. Zachariah and P. E. Pepe, "The development of emergency medical dispatch in the USA: a historical perspective," vol. 2, no. 3, pp. 109–112, place: England. [Online]. Available: https://go.exlibris.link/cwRwjW0q

[19] American Society of Testing and Materials, "ASTM f1552-94 standard practice for training instructor qualification and certification eligibility of emergency medical dispatchers." [Online]. Available: https://cdn.emergencydispatch.org/iaed/img/how-it-works-best/ASTM%20F-1552-94.pdf

[20] D. Cave, "Standards dictate the level of knowledge and expertise required of students and instructors." vol. 86, no. 1, pp. 40–42. [Online]. Available: https://www.apcointl.org/~documents/article/cde-54560-emd-standards

[21] American Society of Testing and Materials, "ASTM f1258–95 (reapproved 2001) standard practice for emergency medical dispatch."

[22] A. Clawson, P. Stewart, C. Olola, S. Frietag, and J. Clawson, "Public expectations of receiving telephone pre-arrival instructions from emergency medical dispatchers at 3 decades post origination at first scripted site," pp. 34–39. [Online]. Available: https://cdn.emergencydispatch.org/iaed/pdf/Public_Expectations_of_Receiving_Telephone_Pre-Arrival_Instructionsfrom_MPDSScripted_Site.pdf

[23] J. J. Clawson, K. B. Dernocoeur, and C. Murray, *Principles of emergency medical dispatch*, 6th ed. Priority Press, OCLC: 959982762.

[24] J. Clawson, D. Jorgensen, A. Fraizer, I. Gardett, G. Scott, B. Hawkins, W. A. Maggiore, and C. Olola, "Litigation and adverse incidents," vol. 6, no. 2, pp. 3–11.

[25] N. Singh, N. Roy, and A. Gangopadhyay, "Analyzing the emotions of crowd for improving the emergency response services," vol. 58, p. 101018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1574119218305479

[26] C. Reuter and J. Schröter, "Microblogging during the european floods 2013: What twitter may contribute in german emergencies," vol. 7, no. 1, pp. 22–41, publisher: IGI Global. [Online]. Available: https://www-igi-global-com.uc.idm.oclc.org/gateway/article/www.igi-global.com/gateway/article/142941

[27] A. Newcomb. Social media is playing an important role in harvey rescue and relief. [Online]. Available: https://www.nbcnews.com/tech/social-media/social-media-becomes-savior-hurricane-harvey-relief-n796701

[28] J. Li, K. K. Stephens, Y. Zhu, and D. Murthy, "Using social media to call for help in hurricane harvey: Bonding emotion, culture, and community relationships," vol. 38, p. 101212. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2212420918314961

[29] Using twitter to connect communities. [Online]. Available: https://developer.twitter.com/en/use-cases/build-for-good

[30] C. Page-Tan, "The role of social media in disaster recovery following hurricane harvey," vol. 18, no. 1, pp. 93–123, publisher: De Gruyter. [Online]. Available: https://www.degruyter.com/document/doi/10.1515/jhsem-2018-0054/html

[31] F. Laylavi, A. Rajabifard, and M. Kalantari, "Event relatedness assessment of twitter messages for emergency response," vol. 53, no. 1, pp. 266–280. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306457316303922

[32] National Emergency Number Association (NENA) and Agency Systems Committee, DocumentReview Working Group, "Recommended generic standards for e9-1-1 PSAP intelligent workstations." [Online]. Available: https://cdn.ymaws.com/www.nena.org/resource/resmgr/standards/NENA-STA-028.2_(orig_04-004).pdf

[33] National Emergency Number Association (NENA), Agency Systems Committee,, and EIDO JSON Working Group, "NENA standard for emergency incident data object (EIDO)." [Online]. Available: https://cdn.ymaws.com/www.nena.org/resource/resmgr/standards/nena-sta-021.1_eido_json_202.pdf

[34] Fire & rescue calls for service. [Online]. Available: https://insights.cincinnati-oh.gov/stories/s/Fire-Rescue-Calls-for-Service/6jrc-cmn5/

[35] CDC. CDC museum COVID-19 timeline. [Online]. Available: https://www.cdc.gov/museum/timeline/covid19.html

[36] A. E. Smithson and L.-A. Levy, "Ataxia: the chemical and biological terrorism threat and the US response," publisher: Henry L. Stimson Center Washington, DC.

[37] NLTK stop words. [Online]. Available: https://pythonspot.com/nltk-stop-words/

[38] I. Temnikova, C. Castillo, and S. Vieweg, "EMTerms 1.0: A terminological resource for crisis tweets."

[39] A. Olteanu, C. Castillo, F. Diaz, and S. Vieweg, "CrisisLex: A lexicon for collecting and filtering microblogged communications in crises," in *Proceedings of the 8th International AAAI Conference on Weblogs and Social Media (ICWSM'14)*. AAAI Press, meeting Name: 8th International AAAI Conference on Weblogs and Social Media (ICWSM'14).

[40] "Discovering health topics in social media using topic models," publisher: figshare Type: dataset. [Online]. Available: https://figshare.com/articles/dataset/Discovering_health_topics_in_social_media_using_topic_models/1007712/5

[41] Twitter4j - a java library for the twitter API. [Online]. Available: https://twitter4j.org/en/index.html

[42] Twitter usage statistics - internet live stats. [Online]. Available: https://www.internetlivestats.com/twitter-statistics/

[43] Guidecards. [Online]. Available: https://www.apcointl.org/services/guidecards/

A Example EMD Guide Card

Allergic Reaction

Vital Points Questions

Is the patient breathing normally?
Difficulty breathing?
Is the patient having difficulty swallowing?
Is the patient's tongue, lips, throat, or face swollen?
Is the patient able to speak in full sentences?
Is the patient feeling faint or has fainted?
Has the patient used an EPI-Pen?
If YES, **Go to Pre-Arrival Instructions**
If NO, **Continue**
What is the patient complaining of?
What is causing the allergic reaction?
Was it gradual or sudden onset?
Does the patient have a history of reaction to anything?
If YES, what?
Does the patient have a rash or hives?
If unknown, expose the back or abdomen to verify.
Are the symptoms getting worse?
Is the patient wearing a MEDIC ALERT bracelet or Tattoo?
If YES, what does it say?
Does the patient have any medical or surgical problems?
If YES, what are they?

Pre-Arrival Instructions

If unconscious and not breathing, go to *CPR* for the appropriate age group. Trained bystanders may still need instructions. ***ASK IF THEY NEED INSTRUCTION?***
If unconscious, go to *AIRWAY CONTROL instructions.*
• When a reaction kit is to be used, and if a bystander feels comfortable assisting, **use as the physician has directed.**
• Have the patient rest in the most comfortable position.
• Keep the neck straight -- remove any pillows.
• Keep calm.
• If a stinger is visible, brush off, if possible. (do not grasp)
• Ice the sting. Do not place ice directly on the skin - use a cloth or other suitable material.
• Nothing to eat or drink.
If Applicable:
• Gather patient's medications and give to responders when they arrive.
• Put any pets away.
• Turn the outside light on and/or wait at the door.
If anything changes or the patient's condition worsens, please call back.

Dispatch Priorities

ALS Priority
Unconscious a/o not breathing normally/difficulty breathing
Difficulty breathing or swallowing
Swelling of tongue, lips, throat, or face
Cannot talk in full sentences
Fainting (syncope)
Epi-pen (Epinephrine) has been used
Sudden
History of immediate severe reaction
BLS Priority
Itching, hives, and/or no breathing difficulty
History of severe reaction but none now
Call delayed longer than 30 minutes with a history of reaction without other medical symptoms
Reaction to medication, no other critical criteria
BLS Standard
Concern about reaction, but no history
Reaction present for a long time (greater than 1 hour), no difficulty breathing

Figure A.1:
An example of a guide card showing how to question a caller (top left), instruct on medical aid (top right), as well as the priority and resources to be sent (43).

B Keyword and filter word relationship lists

Heart-Related Keywords and filter words

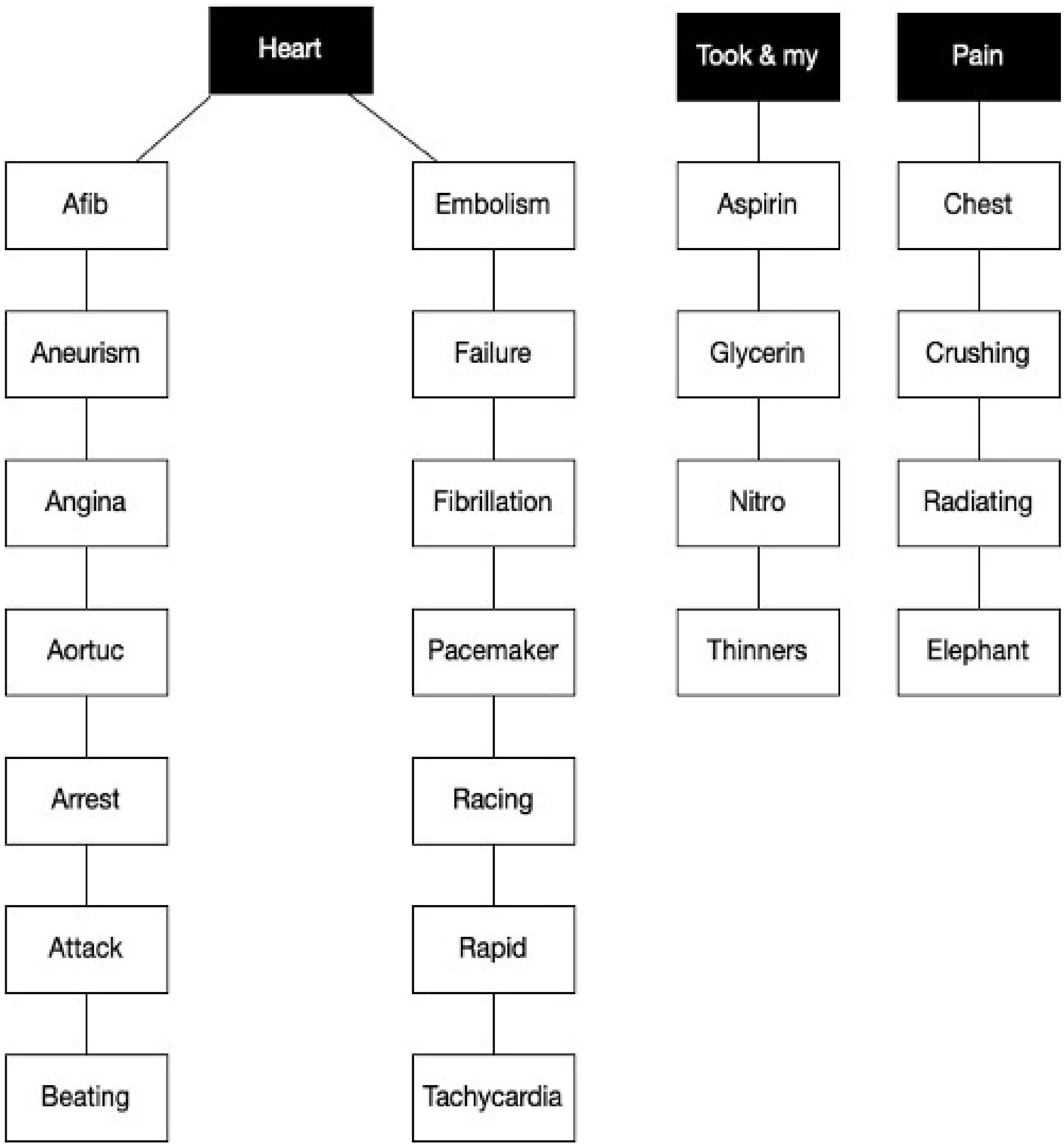

Figure B.1:

For heart-related concepts, the tweets must contain one keyword (in black boxes), and optionally a filter word (in white boxes). These calls for service were the most straightforward, and only required the pairing of words.

Breathing Keywords and filter words

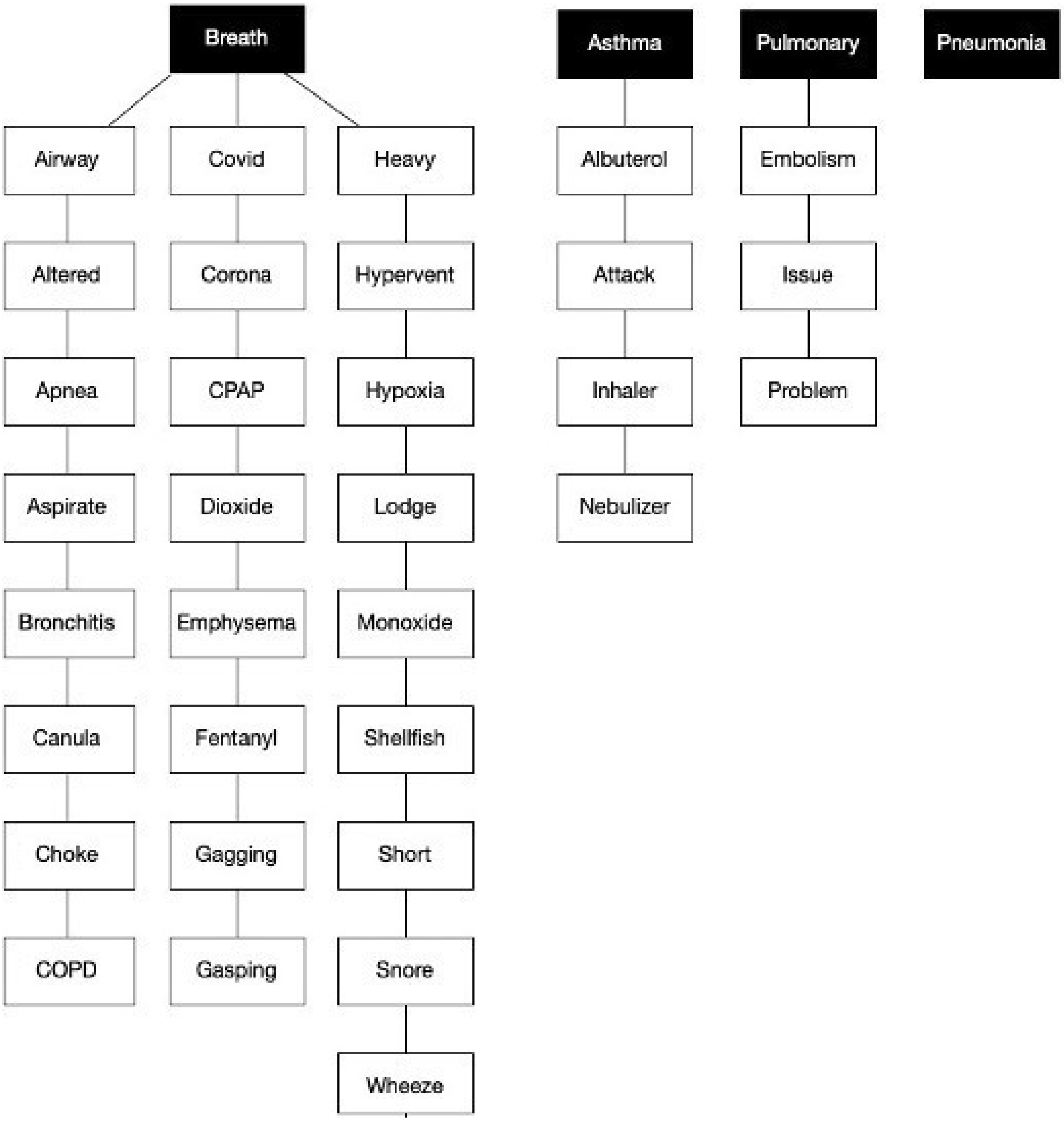

Figure B.2:
For breathing-related concepts, the tweets must contain one keyword (in black boxes). For more restrictive searching, a filter word (white box) also had to be present. The only exception is pneumonia, since this word was found with no word pairings, it always stood alone, and needed no filter word no matter how restrictive.

Multiple complaint Keywords and filter words

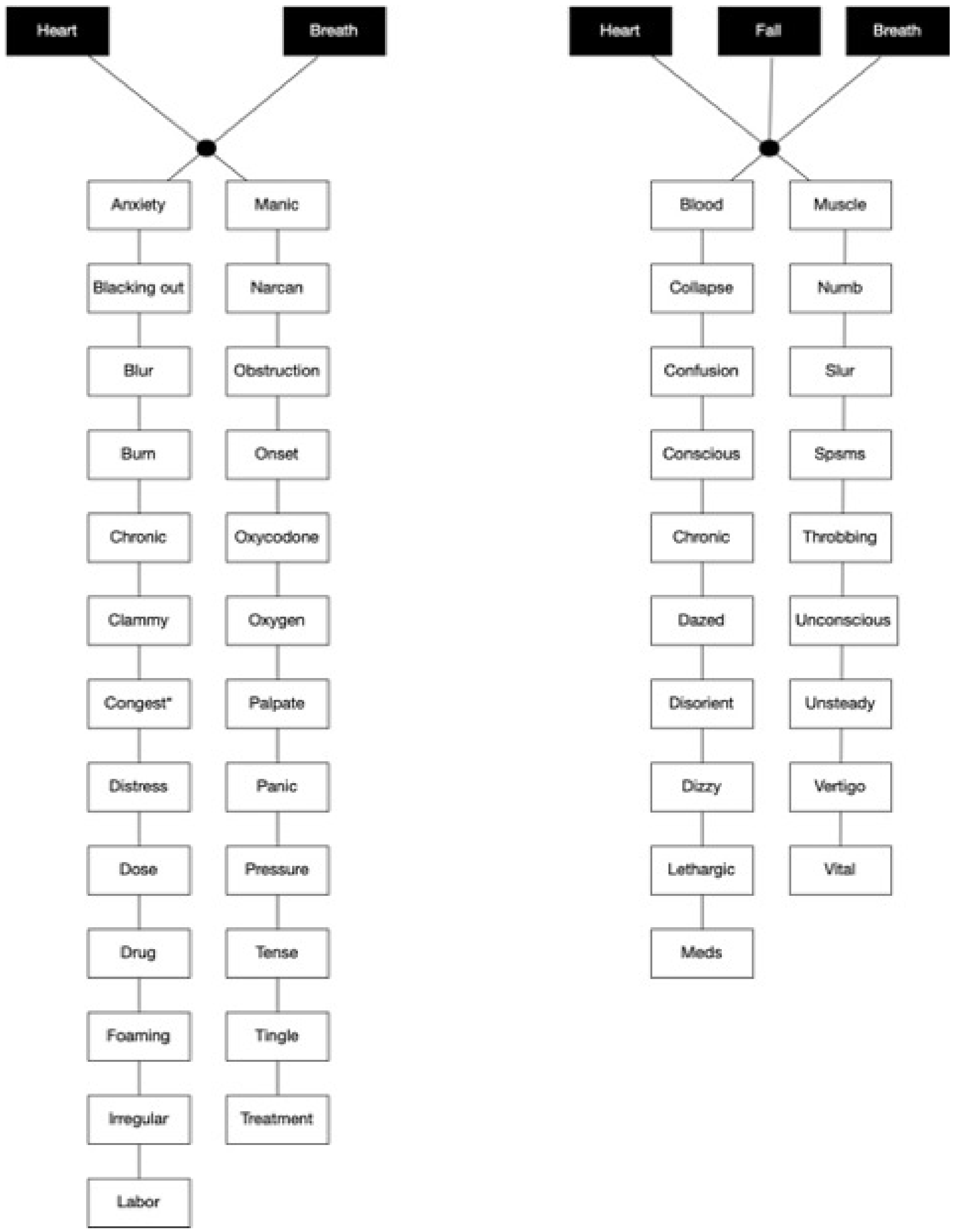

Figure B.3:

In these sets of words, the same filter words were found to apply to multiple keywords. The method used for extracting tweets was the same as the breathing and heart word lists, one keyword (black boxes) was required for a tweet to be selected. Then, if the filtering method was restrictive, one or more filter words (white box) had to be present.

Fall Keywords and filter words

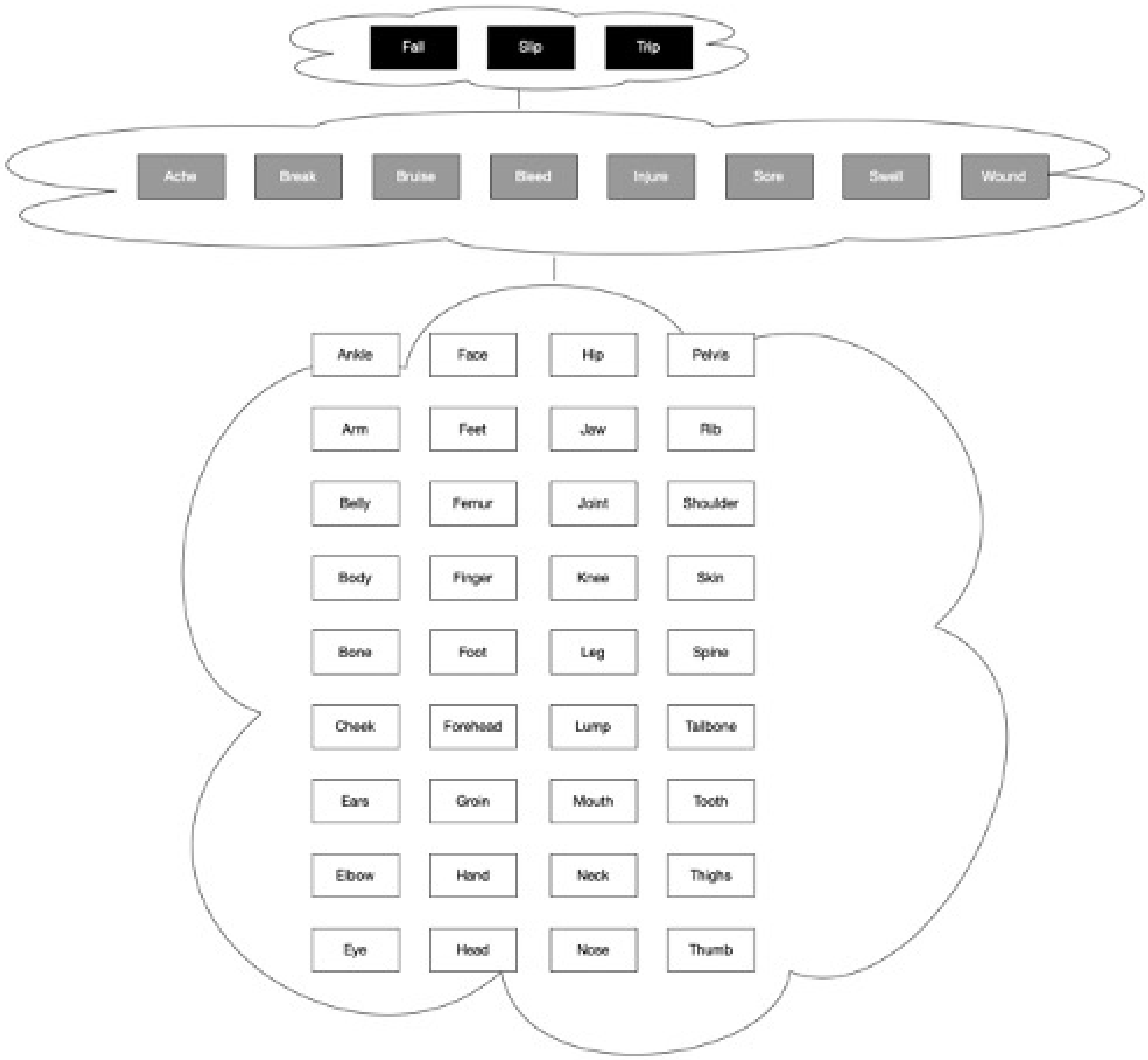

Figure B.4:

Fall keywords presented a challenge since multiple words were used interchangeably. Additionally, many tweets had terms like "my heart fell" when discussing relationship issues. To assure the tweets extracted were related to physical injury, I used a different method for filtering.

In these cases, a tweet had to contain a keyword (black box) but also had to have a modifier regarding physical injury (grey box). Then, if a more restrictive search was needed, one or more filter words (white box) had to be present.