Detection, Categorization, and Comparison of Needs Expressed on Twitter during Crises

Abstract

The Ukraine-Russia Conflict has brought sizable detrimental impact to the global energy, food, finance, and manufacturing industries. In this study, we use Twitter data to automatically identify who needs what and how types of needs, that we categorized and standardized, have evolved throughout the Ukraine-Russia conflict. We observed that the Ukraine needs weapons, Russia says they need land, Europe needs gas, and America sees a need for leadership. As the war prolongs, the need to justify this war evolves along with needs for material goods. Our results show that the majority of needs expressed on Twitter during the conflict are related to transportation, military, health & medical, financial/-money, energy, and essential items (food, water, shelter, nonfood items). Needs fluctuated as the conflict escalated or fell into stalemate. Our comparison of needs across three different disaster domains, namely this war, an earthquake, and the COVID-19 pandemic, showed how needs differ depending on the nature of the crisis, and how domain-adjustment of needs category schema can be done. We empirically contribute to the existing crisis informatics literature by: (1) validating a methodology for using Twitter data to study the demand and supply of things that different stakeholders need during crisis events, (2) testing, comparing, and improving the fit of widely used need classification schemas for studying crisis from different domains.

Introduction

Reliably identifying and prioritizing the needs of impacted populations in a timely manner is critical in crisis response situations to respond to needs and minimize the damages generated as a result of the disaster. Social media platforms such as Twitter have been crucial for extracting relevant situational awareness information about affected and at-risk populations and their needs at any given point in time of a crisis (Sarol et al. 2020; Purohit et al. 2014; Basu et al. 2019). During the Ukraine-Russia conflict, Twitter (along with other social media platforms such as Telegram) has been actively used, for example, by Ukrainian President Zelensky to provide the country's citizens with daily situational updates (Serafin 2022). Refugees who were displaced from their homes in the Ukraine used social media to call for financial assistance and emotional support (Talabi et al. 2022), as well as to share their difficult journeys (Hanley, Kumar, and Durumeric 2022). Twitter users from other European nations such as Poland and the United Kingdom (Lewandowska-Tomaszczyk 2022) have shared messages of emotional support as well as calls for donations and financial aid for Ukrainian refugees.

Methods to detect expressions of resource needs and availabilities from Twitter content have only been applied to natural and biological crisis events such as the 2010 Haiti earthquake (Sarol, Dinh, and Diesner 2021a), the 2015 Chennai floods (Sarkar, Roy, and Basu 2019), and the COVID-19 pandemic (Sarol et al. 2020). In this paper, we apply a prior natural language processing (NLP)-based needs detection method to data about the Ukraine-Russia conflict and extend this methodology to capture how needs evolve over time in this particular context. Our longitudinal examination of needs acts as a proxy for a crisis timeline as it shows if and how needs change over time as this particular conflict unfolds. Given the continued violence and escalation of this conflict, we expect the demand and supply of needed material and immaterial needs to change to adapt to the changing situation. Our methodology includes three steps: First, extracting terms that represent "needs" and "supplies" in the word embedding space. Second, extracting who-needs-what triples to determine entities and the specific resources /services they need. Third, coding indicator terms of needs into domain-adjusted categories, including domain-adaptation of two existing needs category schemas that had been developed by others for natural crisis events. We use this methodology to address the following three research questions:

- RQ1: What needs to Twitter users express in the context of the Ukraine-Russia conflict?
- RQ2: How do these needs change over time?
- RQ3: How do needs expressed in a warfare situation compare to other types of disaster, namely natural disasters and a biological crisis?

This study makes two contributions. First, our longitudinal analysis of needs reveals that tracing needs over time serve as a proxy for disaster timelines. For example, a surge of military needs (e.g. weapons, armaments) may imply an escalation of armed conflicts. Second, we show how existing need categorization schemas align with the needs detected by our method and in our context, and what kind of domain-adaptation of these schemas is needed. For example, Military and Financial/Money are not included in official disaster response schemas (e.g., FEMA and OCHA) and the robustness of these schemas is not always consistent. Our findings have implications for adopting NLP approaches in understanding the evolution of a crisis using social media data, and can inform policy development of domain-specific disaster response guidelines.

Related Work

Prior literature in crisis informatics has shown how NLP methods can help to detect relevant crisis-related information such as information about affected individuals and their locations (Olteanu, Vieweg, and Castillo 2015), infrastructural damages (Ashktorab et al. 2014), and immediate needs expressed by vulnerable populations (Sarol, Dinh, and Diesner 2021b; Purohit et al. 2014; Basu et al. 2019). Such information can help crisis responders in their work and to facilitate the review of response effectiveness. A common theme across these studies is the focus on detecting reliable information about affected individuals and/ or communities so that responders can prioritize relief efforts with respect to the urgency of a need (Varga et al. 2013; Sarol, Dinh, and Diesner 2021b). For instance, Sarol, Dinh, and Diesner (2021b) in their examination of needs during the 2010 Haiti earthquake found that priorities related to livelihoods such as food, water, and medical equipment are salient in tweets. Another analysis of tweets about eight natural disaster events by Imran, Mitra, and Castillo (2016) also found that 22% of the expressed urgent needs pertained to essentials such as food, water, clothing, and medical aid. Other studies have match urgent needs to resource availabilities as uttered in social media content, which helps to match needs to supplies (Purohit et al. 2014; Basu et al. 2018). Purohit et al. (2014) built a binary classifier that separates tweets into either requests for or offers of help with respect to resources such as money, clothing, food, medical aid, shelter, volunteer work, and achieved accuracy of 82% and 75% for request and offer, respectively. Basu et al. (2018) identified top needs and availabilities of resources to support humanitarian assistance and disaster relief work during the 2015 Nepal Earthquake using word embeddings and extracted words closest to the terms "needs" and "supplies". Their proposed methodology for matching needs and availabilities achieved an accuracy of 86%. Overall, these studies have demonstrated the feasibility and relevance of detecting needs as well as resources available to meet these needs from social media content generated during crisis events.

The ongoing 2022 Ukraine-Russia conflict is a prime example of a crisis event where social media plays a major role for citizens and netizens to share and get information about the situation on-site in the Ukraine, (Talabi et al. 2022; Hanley, Kumar, and Durumeric 2022), for family members to connect with each other (Serafin 2022), and for political groups to launch campaigns (e.g. *Ghost of Kyiv*), with the latter possibly contributing to online disinformation (Smart et al. 2022). The negative impact of the war, such as lack of adequate housing and healthcare for Ukrainian refugees (Maggioni et al. 2022) and disruptions in the global supply chains for food (Behnassi and El Haiba 2022) and energy (Orhan 2022) has continued continues since February 2022. According to prior literature, timely detection and prioritization of resource needed is crucial to reduce harmful effects of a crisis (Hiltz and Plotnick 2013; Ashktorab et al. 2014). We aim to contribute to a better understanding of this and possibly future crisis by using NLP and ontology mapping to detect needs with high urgency. We further expand needs detection by tracing changes in needs over time, and determine if there are certain needs which might be missing from existing disaster response guidelines (e.g., financial/money). Finally, we examine the utility of our extended needs detection method by comparing the top needs detected for the Ukraine-Russia conflict to two others contexts, namely a natural (i.e., Haiti earthquake) and a biological (COVID-19 pandemic) disaster, showing that needs detection tasks are highly domain-dependent, and require adjustment of needs category schema to ensure reliability of results.

Data

We rehydrated a dataset from Chen and Ferrara (2022). Their dataset contains 454,488,445 tweet Ids collected from February 22, 2022, through October 01, 2022. The tweets were pulled based on the existence of a keyword relate to the Russia-Ukraine conflict. Examples of these keywords include, but are not limited to: *Ukraine, Russia, Zelensky*. 70.65% or roughly 321 million tweets were in English. Tweet Ids are a numeric code that can be used to request available information tied to a specific Tweet.

To obtain the tweet text and available meta data, we used Twarc for rehydration; a process in which the Twitter API is used to pull a tweet given its unique key identifier. An Id is passed in and a Tweet is returned in a nested json format. Academic access to the Twitter API grants a user access to pulling 10 million Tweets per month. Therefore, we used a 10 million Ids subset of the dataset. To preserve the distribution of tweets, we took the number of Ids for each day, multiplied that number by 10 million, and divided the result by the total size of the data set. We then randomly sampled that percentage of Ids from the corresponding day.

The collection of the subset of Twitter data took four days. After removing non-English and deleted tweets, 5,822,234 tweets remained. The dataset includes tweets posted by 2,310,347 users from 2/25/2022 (the second day after the outbreak of the war) to 9/30/2022.

To estimate the percentage of Tweets posted by bots, we further sampled 1,000 Twitter accounts and used their corresponding meta data and tweets to predict the possibility of being automated accounts. We used the Botometer API (Sayyadiharikandeh et al. 2020) and found that 82% accounts are not bots (as the distribution of scores indicates a cut-off with a threshold of 0.7 (Yang, Ferrara, and Menczer 2022)). As the Botometer has a limit number of API call per account, we can not verify all the Twitter accounts used in this study, which is a limitation of our study.

To compare needs expressed and identified across different disaster contexts, we also implemented needs detection on two existing datasets: COVID-19 tweets [reference omitted for blind review] , and 2010 Haiti earthquake tweets [reference omitted for blind review]. The COVID-19 tweets dataset contains 665,667 English tweets that were posted from February 28 to May 8, 2020. The authors collected tweets that contained at least one of the hashtags, such as #COVID19, #COVID-19, #coronavirusoutbreak.

The 2010 Haiti earthquake dataset contains 54,660 English tweets that were posted between January 12 and June 1, 2010, which corresponded to the immediate response to early recovery phases of earthquake response. The authors collected tweets that contained the keyword "haiti earthquake", or hashtags #haiti, #haitiearthquake during the specified timeframe of data collection.

Methods

Extraction of Needs

Word-embedding Approach To determine what needs were expressed, we applied a word embedding-based approach to extract a list of needs using the seed words "needs" and "supplies", following (Sarol et al. 2020; Sarol, Dinh, and Diesner 2021a). The approach involves four steps:

1. Applying phrase detection models to annotate the dataset using AutoPhrase (Shang et al. 2019) method with a threshold of 0.8.
2. Removing @RT_username, replacing full url links with "URL", splitting tweets into sentences, and tokenizing sentences.
3. Applying word2vec model on the sentences from Step 2.
4. Retrieving and list-ranking the top 100 nouns closest to the word embeddings of needs and supplies based on cosine similarity.

Need Categorization We further applied open and axial coding to categorize expressions of needs within their context of use. First, two coders independently labeled our top 100 need words into categories defined by each coder, along with notes on their rationale for each (category and) assignment. Both coders leveraged the same two existing categorizations of needs, namely (OCHA (2022)'s seven categories of needs and FEMA (2019)'s seven community lifelines) as reference points to develop their own self-generated categories. The categories from OCHA are: *Education, Protection, Food Security and Livelihoods, Shelter and Non-Food Items, Health, Water,* and *Sanitation and Hygiene (WASH)*. The seven categories from FEMA are: *Safety and Security, Food and Water and Shelter, Health and Medical, Energy, Communications, Transportation,* and *Hazardous Materials*. These two schemas were chosen as reference points as FEMA's community lifelines has been the standard for U.S. governmental agencies to prioritize response efforts, and OCHA's needs schema was created based on events that happened (and are happening) in Ukraine as a result of the conflict. The two coders then cross-validated their annotations and reconciled their disagreements until all annotations aligned.

Extraction of Who-Need-What

In addition to extracting and categorizing needs, we also applied a rule-based approach to extract {who, need, what} triples (Sarol et al. 2020), where who represents requesters and what represents resources and/ or targets. We used the syntactic structure of sentences to extract these triples. The method involves the following steps:

1. Apply dependency parser from spaCy (Honnibal and Montani 2017) to tokenized sentences
2. Find "need" terms in sentences.
3. Extract subject (who) and direct object (what) from sentences where the "need" term is a noun.
4. If the "need" term is a verb, extract the descendant of the need term (what), which links through a preposition, and the copular verb of the need term. We use the left child of the copular verb term as who term.

We saw that different from other types of disasters, such as natural disasters or pandemics, warfare includes a more complex set of stakeholders with diverse needs. We used the extracted who-need-what triples to study who the stakeholders are and what needs they express.

Results

RQ1: Needs and Needs Categorization

Need Categorization Our open coding process generated seven categories: **Generic, Military, Transportation, Health and Medical, Financial and Money, Energy, and Food Water Shelter and Non-Food Items**. These seven categories match three categories **Transportation**, **Health & Medical**, and **Energy** from FEMA, and one that merges FEMA's *Food, Water, Shelter* with OCHA's *Shelter & Non-Food Items* to **Food, Water, Shelter, and Non-Food Items**. The new categories we identified are **Military**, **Financial, and Money**, and **Generic**. Generic needs are expressions of needs (true positives), but on the level of abstract concepts or under-specified expressions, such as *assistance*, and phrases that need a reference object, for example: *plans* (for what?) or *purchases* (of what?). Additionally, we included needs for which it was unclear as to who or what they were here, such as *efforts, dependence*, and *incentives*.

We grouped the needs that are not categorized as Military or Generic as supply needs. These needs are physical supplies that could be used for civilian aid purposes, for example: **medicines, cheques, mineral resources, and grains**. Supply needs also include Transportation that allows for the acquisition of material supplies, such as *shipments* or *exports*.

Military needs directly relate to military purposes, for example: weapons and ammunitions. Additionally, needs that are more general but pertain to responsibilities or goals of the military, such as *defense*, were included in this group. Many tweets containing *air* reference anti-air or air defense, and thus were included here as well.

Who Needs What We extracted 33,305 Who-Needs-What triples from our dataset. We excluded sentences that missed either the Who or What part in a tweet. We validated the

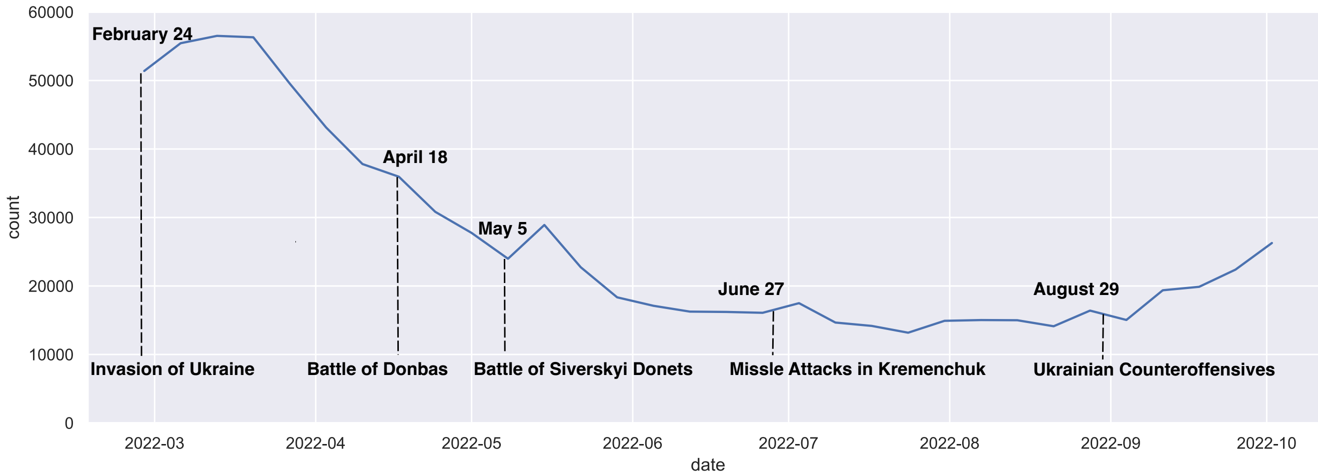

Figure 1: Overall change of needs over time

accuracy of the extracted triples by sampling 100 of the extracted triples, then asked two annotators to independently annotate and verify the triples. For the incorrectly-labelled triples, we further analyzed the errors. The overall accuracy of the automated Who-Needs-What approach was 0.88. Among the 12 erroneous triples in our samples, we saw five types of errors, inlcuding *negation*, mislabeling of *what*, mislabeling of *who*, and incomplete labeling. Six triples were instances of the *negation* error type, which mis-identified **don't need** as **need**, for example: "Russia...don't need anything from the west". Four triples had incorrect/incomplete *what* parts, for example: mis-annotating quantity as *what* in sentence "...Turkey need huge quantity of wheat...". One triple had an incorrect *who* part, mis-annotating people as who in the clause "...funds will go for people who need medicines in hospital...". One triple was extracted from an incomplete sentence which yielded incorrect results from syntactic parsing.

Further, we analyzed the top needs per different stakeholder groups (i.e. the *who* in the extracted triple). Table 1 shows the 30 most frequent {who, need, what} triples with the proportion of that need for the who subject. This result shows different needs (if applicable) across different major stakeholder groups in the Ukraine-Russia conflict. A majority of *who* entities were non-named entities or common nouns, such as *we*, *they*, *people*, *refugees*, who also expressed a need for *help* - a generic category as well. Non-generic *who* entities such as *ukraine* and *putin* mentioned specific resources that were helpful for warfare and situational awareness; the needs for **weapons** accounted for 40% of all the requests from **Ukraine**, which indicates an urgent military weapons shortage from the Ukrainian side. The need for land accounted for 29% of needs for *russians*, which may imply a narrative around the motivation of Russia to escalate the conflict. *Europe* needs *gas* (16%), while *America* asked for *leaders* (25%). The change in what material supplies are needed, such as *weapons*, *money*, and *gas* to abstract or generic needs such as *answers*, *response*, and *support* suggests an evolving nature of this conflict where the need for justification of this war is increasing along with other resource needs.

Table 1: Top needs per different stakeholder groups

Who	What	Ratio	Who	What	Ratio
ukraine	weapons	40% (2,553)	americans	answers	53% (50)
we	help	8% (658)	he	money	6% (48)
they	help	10% (282)	pets	care	92% (46)
i	ammunition	19% (262)	world	victory	9% (45)
people	help	25% (173)	children	peace	37% (44)
putin	ramp	20% (151)	ukrainians	artillery	19% (43)
refugees	help	43% (144)	america	leaders	25% (32)
russia	change	16% (142)	anyone	proof	25% (29)
who	help	13% (110)	europe	gas	16% (27)
you	proof	6% (106)	joe	ar-15	68% (26)
it	response	17% (102)	photos	words	100% (25)
soldiers	help	74% (81)	mariupol	evacuation	55% (22)
russians	land	29% (59)	un	support	68% (21)
that	help	14% (57)	animals	help	64% (21)
zoo	help	100% (53)	minister-ukraine	weapons	78% (21)

RQ2: Change in needs over time

Figure 1 shows how cumulative expressions of needs evolve over time. The heavy left-skewed distribution suggests that there are more requests of needs in the early months of the conflict. This can be for one of two reasons. First, at the onset of a disaster or conflict, the event received frequent media coverage and thus was discussed more on social media. Second, due to the sudden onset of the conflict and initial rapid movement of Russian forces, the Ukrainian military along with crisis responders did not have enough time, resources, and structure in place to respond effectively. Therefore, these groups had higher rates of needs at this time.

As the war progressed, expressions of needs dropped to a low in July and August of 2022, and increased again at the beginning of September. There are several spikes in early April, early May, and late June, which reflects major military events such as the Battle of Donbas (April), the Battle of Siverskyi Donets (May), and missile attacks in Kremenchuk (June). As massive Ukrainian counteroffensives started from

August 29th, we observe an increase in needs at the end of August as well. This change of needs trending can become a proxy for people to monitor the overall progress and identify intense conflicts in a long-term large-scale war.

The prevalence of different categories of needs also changed over time in different ways. Figure 2 shows the trends in non-generic needs over time. As we only used the top 100 needs to retrieve tweets, the number of needs is lower than the actual number in these categories. *Transportation*, *Food Security & Livelihoods*, *Health & Medical*, and *Energy* needs follow the trending in Figure 1, which started with high requests at the beginning and then climbed up during escalations. On the other hand, the *Military* and *Financial/Money* needs show a more stable and consistent pattern, which suggest continuously unmet or reemerging needs during the conflict, e.g., due to the shortage of supply and destruction of weapons.

RQ3: Comparison of needs across different crises contexts

Do the needs during a war resemble the needs during a natural crises of the COVID pandemic such NLP models and classifiers can be reliably re-used across scenarios? To answer this question, we started by extracting and coding a total of 300 occurrences of needs across three disaster events (100 need words per category) and found minimal overlaps in the needs expressed per type of crisis (as shown in Figure 3). Table 3 shows the top 20 needs detected for each disaster event. There are six terms in common across all three events: *assistance*, *goods*, *kits*, *medicines*, *plans*, and *resources*. Between the Ukraine-Russian conflict and the Haiti earthquake, there is only one unique overlapping term, namely *items*. However, between the Ukraine-Russian conflict and the COVID-19 pandemic, there are 18 overlapping terms: *ability*, *aid*, *capacity*, *deliveries*, *demands*, *efforts*, *equipment*, *essentials*, *manufacturers*, *medical-equipment*, *necessities*, *packages*, *production*, *purchases*, *shortages*, *supply*, *systems*, and *utilities*. Between COVID-19 pandemic and the Haiti earthquake, there are two overlapping terms, namely *services* and *food*. This suggest that a war and a pandemic lead to more similar needs than a war versus a natural disaster, which has implications for the use of policies and incidence management plans a war. Furthermore, the overlapping needs terms mainly pertain to supply chain related topics (e.g. deliveries, purchases, supply) as well as essential items (e.g. medical equipment, necessities). The six overlapping terms across the three considered events are relatively generic terms that pertain to humanitarian assistance activities and related resources.

Table 2 shows the categories of needs for each event dataset (schema in discussed in *Needs Categorization* section). We include three additional categories (i.e. *other*, *generic*, *not a resource*) for need terms that do not fit into any of the predefined categories. Terms related to ”other” are valid need terms that do not fit in any of our predefined categories, but are important resources for a particular crisis event. For instance, assistance programs such as *paid-sick-leave* and administrative bodies in charge of pandemic response (i.e. *local-governments* are important indicators of needs and/ or responses. ”Generic” are legitimate needs-related terms, but they would need further specification, such as an object, to clearly understand what resources is mentioned. For instance, terms such as *resources*, *requests*, and *donor* signal that some support is needed or available, but they do not indicate the specific area of support. ”Not a resource” are terms that taken out of the context of the original tweet, do not indicate a need. For the Ukraine-Russia conflict, we found six categories of needs mentioned that are consistent with our category schema, with the most frequently-mentioned one being *transportation* (14%), and the two least mentioned categories being *Food, Water, Shelter, & Non-Food Items* (3%) and *Financial/Money* (3%). For the COVID-19 pandemic, we found seven categories of needs that fit into our predefined schema, with the most salient category being *health & medical* (25%). Least frequently-mentioned categories are *safety & security* (1%) and *Energy* (1%). For the Haiti earthquake, we observed four categories of needs, namely *health & medical* (3%), *food, water, shelter, & non-food items* (5%), *safety & security* (3%), and *financial/money* (4%). Across all three events, terms are most frequently labeled as *generic* (59% for Ukraine-Russia conflict, 50% for COVID-19, 68% for Haiti earthquake).

Table 3 presents the top twenty needs extracted for each disaster event. These terms are selected because they are the closest to the term *need* in the word embedding space. For the Ukraine-Russia conflict, top needs seem related to or indicative of supply-chain issues such has *deliveries*, *shipment*, and *exports*. There are also need terms related to essential items for the vulnerable population such as *medicines*, *humanitarian-aid*, *essentials*, though some of these terms are not specific in terms of what types of items they refer to. For the COVID-19, a majority of needs pertain to health and medical equipment such as *personal-protective-equipment* and *medicines*. There are three generic terms that may allude to the needs of essential goods for day-to-day livelihood during lockdown periods (i.e. *essentials*, *essential-items*, *stockpile*. There is also a notable proportion of terms (25%) relating to supply chain topics, such as *supply*, *distribution*, *goods*, *manufacturers*, and *manufacturing*. For the Haiti earthquake, needs are primarily related essential items for livelihood such as *clothing*, *medical-care*, *americares* (healthcare resource), *shelter*, *woods* (for heat). Other terms allude to financial/money-related topics such as *debt*, *services*, *cash*, *pledge* (which may relate to donation campaigns). There are a number of generic terms (e.g. *assistance*, *team*, *agencies*) which may suggest involvement of response organizations but further examination is needed on the context of these terms.

Discussion

The findings from this study show that the extraction of needs from empirical data can lead to the detection of need categories and instances that are not covered in widely used guidelines of disaster response and humanitarian crises, such as OCHA and FEMA. We also showed that the reliable extraction of {who-need-what} triples can capture needs of a broad set of stakeholders involved in a crisis. By apply-

Figure 2: Change in needs per category over time

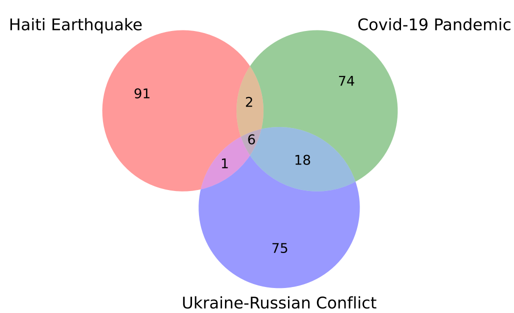

Figure 3: Overlapping of top needs from different disasters

ing a word-embedding approach to a corpus of Twitter data, we were able to extract both generic and specific needs, such as equipment (generic) vs. medical-equipment (specific). {Who-need-what} triples were identified with an accuracy of 0.88 by using a simple dependency parser-based approach.

Using this needs detection approaches, we observed changes in expressions of needs over time that align with the progress of the war. For instance, the Ukraine counteroffensives in Kharkiv started on August 29th, and the overall needs started to increase in later August. The alignment of needs detected from social media data with the events of the war suggests that social media can be a proxy for battlefield progress, which enables the tracking of war-related demands possible using social media data. Moreover, the change of needs also implies potential supply chain shortages. For example, the increasing demands of Energy may intensify the shortage of logistic resources. In future work, we plan to test the usability of needs detection for modeling and analyzing supply chain issues.

Suggestions for Improving Tools for Needs Detection

While our needs detection framework exhibits effectiveness in identifying needs and {who-needs-what} triples, there is space for improvement of extracting useful needs. In our extracted needs list, more than half of the need terms are generic terms, which lack a reference term or object. Though this is natural considering our approach focuses on the closest terms of needs and/ or supplies in a semantic space, we still need a computational solution to connect these generic terms with the corresponding reference objects. In the current priority-needs rank list, most of these specific needs are separately identified and ranked at a lower position than the generic terms. We plan to detect both general and specific needs concurrently to provide users with the opportunity to examine both the “big picture” of a needs situation and tangible resource needs of an affected population. For example, if an NGO wants to raise funding and needs to decide what kinds of supplies they should ship, using a specific needs detection tool can be helpful in providing necessary details. On the other hand, if an authority wants to develop an awareness of the big picture of the war or conflict, a generic needs detection model might be more useful. Furthermore, our qualitative error analysis uncovered potential challenges for developing needs detection tools. We identified errors including negation, mislabeling of what, mislabeling of who,

Table 2: Categorization of needs (with examples) across three different crisis events: Ukraine-Russia Conflict, COVID-19 Pandemic, and Haiti Earthquake

Needs Categories	Ukraine-Russia Conflict		COVID-19		Haiti Earthquake	
	Percentage	Examples	Percentage	Examples	Percentage	Examples
Health & Medical	3%	medicines medical-equipment,	25%	medical-supplies, protective-gear	3%	medicines, medical-care
Food, Water, Shelter, & Non-Food Items	3%	grains, rations	5%	food-banks, groceries	5%	clothing, tents
Transportation	14%	deliveries, shipments	2%	deliveries, distribution	0	0
Military	3%	ammunitions, armaments	2%	defense-production-act, dpa	0	0
Safety & Security	0	0	1%	childcare	3%	mothers, woods
Financial/Money	3%	expenditure, cheques	11%	expenses, grants	4%	charities, debt
Energy	7%	generators, oil	1%	utilities	0	0
Other	0	0	3%	local-governments, paid-sick-leave	10%	worldvision, partners
Too Generic	59%	requests, resources	50%	handouts, assistance	68%	mercy, donor
Not a Resource	8%	taster, mobilizes	0	0	7%	weekend, glance

Table 3: Comparisons of top deeds in different disasters

Ukraine-Russia Conflict	COVID-19	Haiti Earthquake
deliveries	medical-equipment	assistance
shipments	equipment	groups
flows	medical-supplies	long-term
exports	protective-gear	plans
supply	stockpile	disaster-relief
delivery	protective-equipment	catholics
aid	ppe	cash
transfers	manufacturing	agencies
suppliers	personal-protective-equipment	debt
alternatives	medicines	services
medicines	#ppe	tiger
equipments	supply	clothing
humanitarian-aid	distribution	reconstruction
ammunitions	goods	woods
supplie	manufacturers	respond
sales	funds	team
essentials	plans	pledge
plans	essentials	americares
provision	essential-items	medical-care
terminal	financial-relief	shelter

and incomplete labeling. Negation errors could be addressed by crafting more sophisticated rules and in-domain annotations (Wu et al. 2014). To address incomplete labeling errors, distantly-supervised NER tools (Meng et al. 2021) can be a potential solution to integrate to improve *Who* and *What* quality. Alternatively, a taxonomy with a comprehensive list of potential resource asks might help making needs detection tool more transparent and robust. For example, a taxonomy combining the guidelines from FEMA, OCHA, CDC, and other authorities could allow people or jurisdictions to directly match their needs with supplies from corresponding disaster response organizations.

Using Needs as Proxy of Conflict Progress

Online social media data can be an effective (supplemental) source for monitoring the progress of armed conflicts. Though previous research has focused on using Twitter data to track the progress of natural disasters such as hurricane, riots, and earthquakes (Gupta, Joshi, and Kumaraguru 2012), and man-made disaster such as regional conflict (Azam et al. 2015), there is a sustained need to understand how social media data can be used monitor massive long-term international armed conflicts that include multiple stakeholders and significant consequences. This study on the different aspects of needs expressed related to the Ukraine-Russia conflict adds to the existing literature on social media data-mining and crisis informatics.

Our extracted {who, need, what} triples reflect the needs of different parties from political entities (e.g., ukraine) to geopolitical regions (e.g., europe), frontline roles (e.g., soldiers) to affected population (e.g., refugees), and specific politicians (e.g., Putin) to international organizations (e.g., UN). We observed a number of needs containing Twitter users' hope for explanations and justifications about the conflict. For example, {Americans, need, answers} is not a specific need from Americans people but more like an anticipation for explanations from the government of involving in the conflict. This observation aligns with previous work (Suh et al. 2021) of using social media data to study the public's hierarchy of needs as a crisis progresses, where the needs moved from physiological/safety to cognitive/self-actualization needs.

The change in needs over time is a proxy of conflict progress. Figure 1 tells not only the change of needs but also the escalation and stalemate of the conflict. For outsiders (e.g., the public and responders) to be able to gain situational awareness of the conflict, including connecting military actions to changes in needs, enables the public to better understand opinions, material supplies and demands, and the position or perspective of various stakeholders. Moreover, if NGOs or disaster response authorities want to prepare resources and raise funding, knowing about needs, of what type they are, and how those change over time can support decision-making.

Needs, as the counterpart of supplies, can also imply potential supply-chain issues on a local to global scale. The high demand of energy from Europe reflects the consequence of the war on gas/oil supplies to European countries. The increase of Military demands may suggest an increased supply-chain pressure on national defense industries of the countries directly or indirectly involved in the conflict (Sciutto et al.). Meanwhile, we can also integrate supply-chain data such as the Purchasing Managers' Index (PMI) to estimate the discrepancy between public needs and market supplies.

Comparing Needs across Disaster Domains

Our third research question asked about the differences in the needs detected across three different disaster domains, namely warfare (Ukraine-Russia conflict), a natural disaster (Haiti earthquake), and a biological disaster (COVID-19 pandemic). We find the highest overlap in need terms between warfare and COVID (18%), and the lowest overlap in need terms between the natural disaster and warfare (1%). The intersection of all three events is 6%, and those needs are for medical resources and humanitarian assistance. The top 20 needs we identified for each disaster event (shown in Table 3) showed minimal overlap in top need terms across events. The prominent themes across top need terms were also different: In the Ukraine-Russia conflict dataset, the top needs were related to logistics and possibly supply chain issues (e.g. exports, supply). In the COVID-19 dataset, a majority of top needs related to health and medical supplies, specifically personal protective equipment and medicines. For the Haiti earthquake, financial/money-related terms were frequently mentioned, indicating the potential urgency of financial aid to support response activities. In fact, Sarol, Dinh, and Diesner (2021b) in their examination of the same dataset also found notable mentions of donations and charity events to help victims of the Haiti earthquake. Need categorization results (as shown in Table 2 reveals that a number of these need terms were valid yet *generic* or broad terms. This could be an artifact of our needs detection algorithm, which we can further refine to extract more specific needs. Another explanation could be that language use on Twitter is short and may contain noise in the content (Schulz, Ristoski, and Paulheim 2013; Sarol, Dinh, and Diesner 2021b), which makes more specific needs detection more difficult. We were surprised to not capture any needs terms pertaining to *safety & security* in the Ukraine-Russia conflict data. We hypothesize that this may be because the definition of safety and security in our category schemas focus on the protection of vulnerable groups (e.g. mothers, children, elderly (OCHA 2022)) as opposed to military-related security activities. This also means that there were no mentions of protected groups in the tweets discussing the Ukraine-Russia conflict in our dataset, which could also be a sampling issue. On the other hand, terms alluding to protected groups such as *mothers* and *childcare* were mentioned in the Haiti earthquake and COVID-19 datasets and were detected by our methodology. Overall, we find that the actual need terms and the categories they belong differ across disaster contexts, and thus adjustment of needs schema is recommended depending on the disaster type.

Conclusion

In this paper, we showed how the reliable detection of needs from Twitter content, including extracting terms that indicate needs and supplies and who-needs-what triples, can help to study the unfolding of the Ukraine-Russia conflict. Our findings show that people express specific and generic needs on social media, and that those needs relate to the progress of the armed conflict. Our comparison of needs extracted from tweet corpora about three different disaster events revealed that needs detection is highly domain-dependent, that a war is more similar to a pandemic than a natural disaster in terms of what's needed, and domain adaption of needs categorization schemas is needed to ensure the reliability of results.

In future work, we plan to enhance our needs detection algorithm to distinguish between generic and specific needs and expand generic needs with additional objects. We plan to further match needs vs supply by integrating multi-source data and developing statistical models to predict discrepancies in supply chains.

Ethical Statement

The dataset in this paper is collected from a publicly-accessible online platform. While our focus is on extracting keywords from tweets and not individual user, such dataset may carry risks for privacy issues. To mitigate these issues and comply with terms of service, we will release only tweet IDs for the dataset used in this study.

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Appendix 1:Top Need List ranked by Similarity

deliveries	resupplies	consumptio	equipment	global-markets
shipments	re-export	requests	items	inventories
flows	stockpiles	transports	generators	expenditure
exports	humanitarian-assistance	components	diversification	self-sufficiency
supply	assistance	subsidies	kits	sells
delivery	production	imports	capacity	supplier
aid	purchases	technological-innovations	medical-equipment	dependance
transfers	costs	brethre	capacities	shortages
suppliers	cheques	willing	manufacturers	transport
alternatives	systems	medicine	efforts	shortfall
medicines	gas-flow	amounts	ability	dictatorships–oil
equipments	goods	grains	spare-parts	delays
humanitarian-aid	armaments	packages	sourcing	pumps
ammunitions	necessities	mobilizes	consumption	gas-flows
supplie	taster	reserves	demands	fertilizers
sales	flow	scarcity	could	asap
essentials	transit	high-performance	mineral-resources	utilities
plans	resources	struggles	wepons	generator
provision	high-grade	interdependency	consignment	raw-materials
terminals	incentives	shipment	ration	producers