Article

Enhancing Artificial Intelligence for Twitter-based Public Discourse on Food Security During the COVID-19 Pandemic

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Abstract:

Objective: Food security during public health emergencies relies on situational awareness of needs and resources. Artificial intelligence (AI) has revolutionized situational awareness during crises, allowing the allocation of resources to needs through machine learning algorithms. Limited research exists monitoring Twitter for changes in the food security-related public discourse during the COVID-19 pandemic. We aim to address that gap with AI by classifying food security topics on Twitter and showing topic frequency per day.

Methods: Tweets were scraped from Twitter from January 2020 through December 2021 using food security keywords. Latent Dirichlet Allocation (LDA) topic modeling was performed, followed by time-series analyses on topic frequency per day.

Results: 237,107 tweets were scraped and classified into topics, including food needs and resources, emergency preparedness and response, and mental/physical health. After the WHO's pandemic declaration, there were relative increases in topic density per day regarding food pantries, food banks, economic and food security crises, essential services, and emergency preparedness advice. Threats to food security in Tigray emerged in 2021.

Conclusions: AI is a powerful yet underused tool to monitor food insecurity on social media. Machine learning tools to improve emergency response should be prioritized, along with measurement of impact. Further food insecurity word patterns testing, as generated by this research, with supervised machine learning models can accelerate the uptake of these tools by policymakers and aid organizations.

Keywords: Food Security, Machine Learning, Topic Modeling, Twitter, Natural Language Processing

Abbreviations: U.S. (United States)), SNAP (Supplemental Nutrition Assistance Program), GPS (Global Positioning System), WIC (SNAP for Women, Infants, and Children), Application Programming Interface (API), Latent Dirichlet Allocation (LDA), artificial intelligence (AI)

1. Introduction

Food insecurity has surged globally during the COVID-19 pandemic.[1] Worldwide, food assistance and distribution remains one of the most basic needs, both in emergency and non-emergency settings. In the United States (U.S.), rates of food insecurity generally have continue to increase, particularly among lower income adults.[2–4] This

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trend has been exacerbated by the COVID-19 pandemic, which caused an unprecedented surge in food insecurity nationwide.[6–8] Since the beginning of the pandemic, an unprecedented number of food banks experienced supply shortages and many were forced to close.[9] Food pantries have traditionally provided critical nutritional resources for clients, especially during disasters in already food insecure populations; however, the magnitude and duration of the COVID-19 pandemic has exposed critical limitations amid unparalleled needs.

Simultaneously, as other fields have applied insights from COVID-19 to mature their real-time situational awareness technologies, these efforts have been notably lacking for food distribution agencies.[5] Notably, other public health fields have employed social listening,[6,7] or the monitoring of social media networks in real time, for trends in topics, sentiments, misinformation, and emerging issues.[8] During the COVID-19 pandemic, public health researchers used social listening to spot and correct COVID-19 misinformation, understand opinions on COVID-19 vaccinations and masks, report emergencies, and track symptoms and emerging cases. In other fields, social listening has been used to combat the *Infodemic*, or the overwhelming amount of information—trustworthy and untrustworthy—that is now found on online platforms.[7,9,10] Both the World Health Organization (WHO) and the United States Centers for Disease Control and Prevention have recently placed an emphasis on further developing these tools in the last couple of years.[7,9–11] The WHO in particular is developing tools to advance real-time social listening that promotes an adaptive public health response and can be iteratively improved as new information is collected.[6]

A strength of these social listening strategies lies in the near ubiquity of social media and digital communications platforms. This level of engagement between peers can drive individual and group-level behavior change.[12] That engagement can in turn be used to shape behaviors via digital 'networking' that reinforces or drives behaviors. To date, these strategies have shown a wide range of successful uses, from diabetes management in adolescents[13] and prevention,[14] to weight reduction[15] and increasing consumer spending through group discounts.[16] Based on these previous findings, scalable digital strategies are urgently needed to promote food assistance use and management.

A more advanced tool for social listening is machine learning. Machine learning algorithms, a subset of artificial intelligence, can analyze a body of texts, such as tweets or news media posts, and categorize messages into topics or themes, known as topic modelling.[17] Additionally, other machine learning algorithms can categorize texts based on their positive or negative sentiments.[18] By combining topic modelling with sentiment analysis, public health researchers can gain rapid insight into the current state of thinking and feeling of large populations of the general public—or population segments thereof. [19]

To date, these technologies have seen limited application in the food assistance sector. While there are studies generally focused on classifying needs and resource messages, and predicting needs, few studies have examined food-specific conversations.[20,21] Past challenges in this applied research context have included limited accessibility to machine learning tools outside of computer science. That limitation makes it difficult to adapt algorithms and define parameters that relate to complex and multivariate public health concepts like food security. However, the past five years have seen a marked increase in the use of these technologies, as well as an increase in open access code and software packages that simplify previously arcane knowledge.

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These technologies will help the food assistance sector improve interconnectivity between food banks and those in need, offer cost-effective solutions to overcome funding barriers, and provide stable scaling of a robust distribution network. This is particularly relevant for the scale of the COVID-19 pandemic and potential future disasters that affect lower-income populations.[5,22]

Technological innovation represents a key opportunity to address the disconnect between the need and availability of supplemental nutrition. A recent scoping review of digital tools for emergency food assistance found that the food security sector is lagging behind others in terms of use and research on modern digital technologies to improve situational awareness during disasters.[5] As a follow up to that research, this study explores using artificial intelligence—specifically the machine learning algorithm Latent Dirichlet Allocation (LDA) model—to mine Twitter for relevant tweets and analyze the topics within conversations. The aims of this study were to:

1. Develop and test a Twitter query string to pull all tweets related to food insecurity and food assistance from January 2020 to December 2021.
2. Determine topics within the corpus of pulled tweets by evaluating and iteratively improving an LDA topic model.
3. Perform a time series analysis on frequency of each topic per day on Twitter from 2020 to 2021.

2. Materials and Methods

To assess tweets pertaining to food security on Twitter, a unique search string is required to effectively retrieve relevant Twitter messages. The information retrieval query to the Twitter Application Program Interface (API) was built using a three-prong process: 1) a Scoping literature review; 2) compilation of a table of words used by other studies; and 3) expert stakeholder input to the iterative list. Ten food security stakeholders (2 academics, 5 food policy actors, 3 emergency preparedness experts) provided input into a social media search string regarding food security.

2.1. Data collection

Once the unique string was created, a Python[23] based script was utilized to run a daily pull from the Twitter API from January 1, 2020 through December 31, 2021 (Table 1). The start date was chosen to allow for analysis of Tweets in the months prior to the WHO pandemic declaration on March 11, 2020. Tweets from January 1, 2020 to March 10, 2020 were used as a comparison group, by topic frequency, for the pre-pandemic phase. The methods to request and use the Twitter API have been described previously.[24] Results were collected, analyzed and visualized using Python and a Google Colaboratory[25] notebook. All Google Colaboratory notebooks are available on GitHub.[26] Historic tweets were collected through use of a Twitter (San Francisco, California USA) developer account on the Twitter for Academic Research by the corresponding author.[27]

2.2. Data Preprocessing

After exploratory data analysis, the data was cleaned through deduplication of tweets and removal of retweets, mentions, and URL's. Emojis and other non-characters, extra space, and punctuation were removed, and all letters were converted to lowercase. Stop words, e.g., the/in/or, were removed. Word, bigram, and trigram frequency per document and the entire corpus was calculated and visualized using re,[28] numpy,[29] pandas,[30] gensim,[31] WordCloud,[32] spacy,[33] matplotlib,[34] PIL.[35]

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2.3. Topic Modeling

Unsupervised machine learning, namely Latent Dirichlet allocation (LDA), was used to examine data for patterns. This is a commonly used statistical-based model for exploratory data analysis of previously unseen unstructured textual data.[17,19,36,37] LDA topic modeling is preferred to traditional qualitative approaches because it summarizes textual data at a scale beyond the capacity of human annotation.[36] By deriving a probabilistic clustering, or latent topic distributions, LDA topic models can identify patterns, themes, and structures of the Tweets texts; it enables efficient classification of large bodies of data based on patterns and features. Topic modeling had been widely used to gain a descriptive understating of unstructured Twitter big data in social science research [12].

Using the Latent Dirichlet Allocation (LDA) algorithm, 22 topics in the corpus[26] were analyzed as described by Sharma.[38] In order to select the optimal number of topics to analyze from the corpus, coherence score, alpha, and beta model hyperparameters were calculated on 75% of the corpus as described by Kapadia.[39]

To iteratively improve and understand the 22 generated topics, a series of metrics and visualizations were considered including dominant topics, representative sentences for each topic, distribution of dominant topics within each document, visualization of the most important words that make up each topic, and word cloud images. To understand the importance (or weight) of the keywords in the topics, frequency and density of top topic words, calculations were made using collections and matplotlib packages. If there were words that had higher frequency than weight in multiple topics, this indicated that they were most likely not important to the topic and were added to the list of stop words.[39] To visualize which topics are most discussed in each and all documents, pandas and matplotlib were used to calculate both the number of documents by dominant topic and by topic weightage. Finally, the pyLDAvis package produced a dynamic intertopic distance map (via multidimensional scaling) including a list of the top 30 most salient terms overall and 30 most relevant terms per topic.[38]

2.4. Time series analysis of topics

To determine the change in the nature or content of food security-related Tweets from before the WHO pandemic declaration on March 11, 2020 (i.e., January 2020 – March 10, 2020) versus after, a time series analysis of the number of posts per day per topic was calculated. The Pandas[30] python package was used to calculate a timeseries analysis of the number of posts per day. The Calplot[40] package was used to create a heatmap of the results.

3. Results

3.1 Stakeholder-derived food security search string

Based on stakeholder input, the final search terms were: "food emergency OR food crisis OR food aid OR food need OR food corona OR food rona OR food assistance OR food distribution OR food distribute OR food free OR WIC OR food security OR food insecurity OR food hungry OR #freefood OR #mealservice OR food pantry OR food bank OR covid food."

3.2 Exploratory Data Analysis

The search returned a total of 116,500 tweets from 2020 and 120,607 tweets from 2021 (Figure 1 and Supplementary Table 1). Of the tweets from 2020, there were 919,317 likes, 17,572 quotes, 72,655 replies, and 215,398 retweets. In 2021, there were 1,038,339 likes,

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23,036 quotes, 81,430 replies, and 294,122 retweets. The top five platforms for posting to Twitter for both years are Twitter for iPhone, Twitter for Android, the Twitter Web App, Twitter for iPad, and the OLIO food sharing app (Figure 1). Each OLIO app post includes the hashtags #free, #UnitedKingdom, #food, and #foodwaste. These hashtags were in the top 10 hashtags for both years (Supplementary Table 3). Other popular hashtags included, #COVID19, #TigrayGenocide, #StopTigrayFamine, and #fastfoodies.

During 2020, presidential candidates Donald Trump and Joe Biden were in the top ten mentions list (Supplementary Table 3). Other government officials included @senatemajldr, Speaker Pelosi, and the White House. @Pulte is the family name of a company and philanthropist. In 2021, top mentions included the United Nations, POTUS, Secretary Blinken, Pulte, EU Commission, and the World Food Programme.

The most liked and most retweeted tweet of 2020 was, "Here is a grown man complaining about the free food at an event he's not going to https://t.co/c0wQTfdL71" (Figure 1 and Supplementary Table 4). For 2021, the most liked and retweeted tweet was, "I saw this on FB and it's the best food pantry donation list I've ever seen. Usually posts like this either end up shaming the donor for what they do or don't give, or shaming the receiver for what they do or don't choose to eat. As a former pantry employee, I endorse! https://t.co/GdvAkLHUDY."

3.3 Topic Model Evaluation

The results of the parameter and hyperparameter (coherence score, alpha, and beta) are presented in Supplementary Figure 1. 22 topics were chosen as the optimal topic number with a coherence value of .514. While there were topic numbers with a slightly higher coherence score, these topics either included repeat topics or missed important sub-topics upon examination. Alpha and beta hyperparameters were also optimized at .91.

3.4 Topic Model Results

LDA topic modeling returned the top 30 terms per topic (Table 2). Each topic was labeled based on these terms as well as representative tweets. Table 6 shows the categories, topics, tweet counts per category and topic, and at least one representative tweet for each topic. The categories, described in the subsequent sub-sections, included: (1) food assistance, needs, and resources, (2) emergency preparedness and response, (3) mental and physical health, (4) stay-at-home life, and (5) entertainment.

I. Food Assistance, Needs and Resources

Food assistance needs and resources as a category comprised the dominant category with 31.2% of all tweets (n = 73,924). The United Kingdom-based smartphone application OLIO returned the following prominent tweets in categories related to food sharing: free, foodwaste, meat (n = 21,392). All posts in this category included the hashtags #foodwaste or #free, plus a location. A representative tweet in this category is: "bagels plain 5 pack 14 april donated by Tesco in #London #UnitedKingdom https://t.co/2KitI4TQ4w #foodwaste #free." Other topics in this category include food pantries (family, donate, support; n = 14,987); government assistance (assistance, stamp, program; n = 11,491); food systems (security, grow, system; n = 11,247); pet food (food, buy, feed; n = 8,815); and food banks (food, week, bank; n = 5,992).

II. Emergency Preparedness and Response

Tweets relating to emergency preparedness and response comprised 30.7% (n = 72,783) of all posts. The most dominant topic in this category related to emergency aid following the unrest in Tigray, Ethiopia in 2021, resulting in tweets regarding food insecurity and calls for aid. For example, one user posted, "@GlobalGsts @WHO @DrTedros @OCHA_Ethiopia @GlobalFund @WFP @gavi @ICRC @ICRC_Africa @ifrc @IFRCAfrica @UNDP @UNICEF @UNICEFEthiopia @AfricaCDC Please help the Tigrians with basic humanitarian assistance, such as food water and medicine. Politics will never end." Other

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types of emergencies related to individual financial crises (money, pay, buy; n = 12,561); COVID-19-related food insecurity (insecurity, covid, crisis; n = 10,787); family needs (people, child, care; 9,672); essential services (work, covid, home; 9,170); advice for emergency preparedness (food, water, emergency; n = 8,421); and values (food, people, thing; n = 7,090).

III. Mental and Physical Health

Topics related to mental and physical health compromised 15.8% (n = 37,432) of tweets. Users posted about well-being and nutrition (eat, feel, hungry; n = 13,077); food as self-medication (food, day, today; n = 9,141); food as love (food, give, love; n= 9,082); and recommendations (food, time, year; n = 6,131). Thousands of users posted about using food as a mechanism to feel better during the pandemic (e.g., food as self-medication). For example, "Okay, I just need to start on some food. That might help distract me from whatever this day is throwing at me." Food as love refers to people gifting food as an act of kindness and/or love. For example, "@CielPha52115605 "I'll always be here love" no matter what they go through, he will always be there to give her hugs and buy her food when shes [sic] hungry, let her rest when shes [sic] tired." Recommendation posts include content like: "@streets @thewhicha @ScooterRiderFMX @InsulateLove £90 from dyas -don't get the expensive one unless u can afford it -you don't need to plan -you put the ingredients in the night before -set the timer and come home to delicious healthy food kept warm and sealed on slow cook for hrs."

IV. Stay-At-Home Life

Stay-At-Home Life (n = 31,823, 13.4%) represents tweets pertaining to daily life eating and other types of habits while people were forced to stay at home during the early phases of the pandemic. Of these tweets, messages about hunger were most abundant (eat, feel, hungry; n = 13,117). Hunger in this case does not refer to food insecurity in the literal sense. For example, one user shared, "I'm cold. I'm tired. I'm hungry. Therefore cuddles, a movie and some food delivery sound like a perfect date [right now]." Other topics in this category include food delivery (food, order, call; n = 9,395) and daily eating habits (food, back, leave; n = 9,311).

V. Entertainment

The entertainment category (n = 21,145, 8.9%) includes two topics, free drinks and entertainment (free, drink, watch; n = 12,102) and free/cheap food (food, good, free; n = 9,043). There were 21,145 tweets assigned to this category, representing 8.9% of tweets. Examples of tweets from this category includes, "TACO TUESDAY AT SOHO LOUNGE ITS GOIN UP #FREEFOOD https://t.co/F4jZn7craX" and "anyone else thinks food tastes better when it's free?"

3.5 Time Series Results

The results of the time series analysis were plotted in a heatmap (Figure 2) for January 1, 2020 to December 31, 2021. Five topics clearly showed a sharp increase in posts per day in March 2020. This included food pantries, food banks, individual financial crisis, food insecurity crisis, essential services, and advice for emergency preparedness. Other topics showed a sharp decrease in the number of posts per day, including food sharing via the OLIO app, well-being and nutrition, hunger generally, and free drinks and entertainment. The topics of food systems, daily eating habits, and recommendations remained consistently high over the two-year period. The topic regarding aid for Tigray increased sharply in 2021, especially in the second half of the year.

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4. Discussion

The COVID-19 pandemic has upended nearly all facets of society, including food security. The combination of big data and artificial intelligence has greatly improved situational awareness, but its potential in food security remains underused. This is the first study to explore the food security conversation on Twitter throughout the COVID-19 pandemic using big data and AI. This study also highlights the utility of machine learning to detect needs and resources on Twitter as well as other discourse related to food security. Several salient findings remained relevant throughout the first two-years of the pandemic: the continuous need and requests for philanthropy (e.g., accounts like Pulte), modifications of daily eating habits particularly during periods of social distancing, food systems discussions (e.g., farming, technology, policies, practices), and the ever-present need and utilization of food banks and pantries. In addition, this study was successful at achieving its three aims.

First, this study improved upon previous work on food security topic modeling that used too broad or too narrow searches to retrieve all relevant food security tweets.[41,42] The current study succeeded in defining first a search string, based on a literature review and stakeholder input. Second, this study defined twelve topics and related top 30 salient terms for retrieving food security tweets. The other topics need additional follow up analysis to determine if tweets are related to food insecurity or not. For example, while some tweets in the mental and physical health category are clearly related to food insecurity, others need more context to determine relevance. Identifying key words and parameters that can differentiate between food security and insecurity tweets, as has been done in this study, are vital to future research aiming for real-time analysis of food needs and resources. This labeled data set will be used as the basis for future supervised learning algorithms.

While this progress on food security is valuable, future work can be improved upon by taking guidance from other fields that have made progress on identifying needs and resources on microblogs, even though they are not explicitly focused on food.[42–48] Recent studies have improved performance of classifying needs and resources through the use of key terms mapped to crisis scenarios and the general detection of needs and resources.[49] This includes crisis-related lexicons, e.g., EMTerms[50] and CrisisLex[51], that contain over 7,000 terms used in Twitter to describe various crises. A specific lexicon related to food security terms could be beneficial in disaster and non-disaster settings.

The identification of 12 topics and associated key words that were clearly related to food security will be used as the base data set for additional research. Future work should aim to supplement the irregular or infrequently collected real-time national and global level surveys on food security. This study also shows that Twitter is an excellent source of information on the public's opinion and knowledge the entire disaster lifecycle, including preparedness, response, mitigation, and resilience. Other work supports that social media is an important venue for big data and AI analysis regarding the disaster lifecycle—and that more such research can improve real-time response and preparedness.[52–59]

Food intake has long been associated with mental health and well-being[60–63] so it is unsurprising that the third most popular tweet category involved these themes. During the COVID-19 pandemic, other studies have shown that lock-down periods were associated vicious cycles of increased food insecurity and worse mental health outcomes—like depression and anxiety disorder—and in turn, these disorders lead to more unhealthy eating.[64–68] Observations from the current study supported this cycle of food insecurity, poor mental health, and increased unhealthy eating via increased frequency of tweets

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about fast food, home food delivery as well as isolation, tiredness and anxiety. However, further analysis is needed to distinguish if posts in this category are truly a reflection of food insecurity or not. For example, users posting about being hungry may or may not be food insecure. Nevertheless, our research supports results found elsewhere using surveys and in-depth interviews[66,68] that the declaration of the pandemic and stay-at-home orders had a profound impact on food insecurity as well as mental health, physical health, and daily life.

Additionally, these categories may also reflect a growing demand among public health professionals and stakeholders for updating the concept of 'food security' to 'nutrition security.'[69–71] Nutrition security is an emerging theme in public health that highlights that improving health outcomes can only be achieved by providing nutritious food, not just any food. The results of this study can be used to guide stakeholders in their efforts to target getting nutritious food to those in need by correlating the need to the frequency of posts.

There were relative differences in topic density, as shown by the time series analysis, on Twitter before (January 1-March 10, 2020) and after the WHO declaration of the COVID-19 pandemic (March 11 – December 31, 2021). Based on our analysis of Twitter-based social discourse on food security during COVID-19, topics that increased in frequency included emerging threats to food security (Tigray, food shortages, corruption/warehouse food hoarding, crop threats), fast food and home delivery, aid organizations and donation requests, individual and large-scale economic crises, stimulus checks, stay at home life, and food pantry advertisements. In concordance with these increased discussion points, related accounts also became more engaged in the discussion, including the World Food Programme, the United Nations and the President of the United States (i.e., President Biden). Detecting real-time trends in public food insecurity discourse can fill the gaps of survey-based data, i.e., the USDA's Household Food Security Survey, which had its last update in 2020.

As the pandemic moved from an initial disruption of daily life to an extended response and concurrent recovery, novelty aspects of staying at home, entertainment to abate pandemic boredom, and political overtones dissipated. These findings were noted as politicians and ideas such as free food and drinks occurred less frequently in identified tweets.

4.1 Limitations

This study is subject to several limitations. The complexity of the two main concepts – food assistance and detecting needs and resources – creates many permutations of possibly relevant tweets. While the search was built iteratively and with multiple stakeholder's input, it is possible a subset of relevant tweets was missed. However, more analysis is needed to determine if tweets classified as 'Entertainment,' Mental Health and Well-being,' and 'Daily Eating Habits' are related to food insecurity. For example, users mentioning hunger is not necessarily an indication of food insecurity and the context of such posts must be examined to determine relevancy. Additionally, while our query was not tailored to English language posts, our search terms may have only promoted the retrieval of English language tweets to the exclusion of other languages. Thus, there could be valuable, non-English language posts that were missed. Future work can improve on these limitations by using supervised learning approaches with word embeddings and/or crisis specific features that have been used to in disaster settings to classify tweets into informative versus non-informative and/or, more specifically, into the six needs and resource classes as defined by UNOCHA (United Nations Office for the

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Coordination of Humanitarian Affairs)[72] and resources such as CrisisLex[51] and EM-Terms[50].

While Twitter is a popular site for public discourse, it may not capture some percentage, minor or major, that other social media platforms, such as Instagram, TikTok, or Facebook, may cover. Additionally, our study did not exclude tweets that did not pertain to food security. All topics were analyzed for relevance to the study themes and were deemed related to food assistance; however, some of the results may have been biased by non-relevant tweets. This deliberate choice to seek broader terms sought to better categorize the available evidence, and no extraneous topics appeared in the top 10 words of each topic. By consensus, the topic themes were generated with confidence.

Unsupervised learning algorithms, such as the LDA algorithm used for topic modeling, are known to have limitations, such as lower accuracy of assigning tweets to the correct topic.[37,39,73] For exploratory data analysis, observations, and preliminary detection of topics in an unfamiliar corpus, it is acceptable to use LDA modeling despite these known limitations.[38,39] Future work could take the results of this topic modeling analysis as the basis for feature selection for more accurate, supervised learning algorithms.

Despite these limitations, this study underscores timely gaps in emergency preparedness interventions and response while defining the scope of existing public discourse on food assistance during the first two years of the pandemic.

5. Conclusions

As the pandemic enters year three, real-time big data collection and analysis with artificial intelligence remains important. This study demonstrated how Twitter and artificial intelligence can be leveraged to increase preparedness and response to food insecurity in future disasters in an all-hazards environment. These new solutions to for real-time detection of food needs and resources point to the pressing need for the development of stabile food security programs.9

This study is the first to develop a query string for food security public discourse during the COVID-19 pandemic. Future research could utilize the topic key words associated with food security, as the basis for supervised learning models for detecting real-time food needs, resources, and emerging threats to food security. Other fields have improved their real-time analyses by feeding their base topic model results into more advanced supervised learning algorithms and feature development.41Current platforms for showing food security information are lacking in real-time data, modern user interfaces, and actionable or usable data for policymakers and aid organization to make real-time resource allocation decisions.

As reflected in this study, there are many policy and practice implications. The results of this study show the pressing need to understand resource allocation challenges during emergencies while enhancing public discourse-informed situational awareness and optimizing food insecurity-response strategies. This model can also be useful for understanding emerging threats to food security. For example, this model unexpectedly focused in on the impact of Tigray on public discourse and concern for food security. The topic modeling was also useful in identifying the economic implications of Covid on global, national, and individual financial crises as well as supply and demand and supply chain issues. Stakeholders can also use this modeling to understand public opinion on food security policies and programs.

As global disasters continue to increase due to climate change and political instability, the development and evaluation of tools that address all disaster phases– prevention, preparedness, response, and recovery—are urgently needed. Machine learning tools to improve emergency response should be prioritized, along with rigorous qualitative and quantitative measurement of impact. Further testing of the generated search string with supervised machine learning models as identified by this study will maximize the efficacy and uptake of these promising digital food security tools by policymakers and aid organizations.

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Table 1: Methods Specifications

Step	Details
Twitter Scrape	Call to Twitter API V2 Academic Track
Coding Language	Python
Query	food emergency OR food crisis OR food aid OR food need OR food corona OR food rona OR food assistance OR food distribution OR food distribute OR food free OR WIC OR food security OR food insecurity OR food hungry OR #freefood OR #mealservice OR food pantry OR food bank OR covid food
LDA Modeling Packages	Gensim Sklearn LDA Mallet pyLDAvis
Word Cloud	wordcloud
Time series heatmap	Seaborn Matplotlib
Date Range	Monthly scrapes, January 2020-December 2021

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Table 2: Topics and example tweets, 2020-2021

I. Food Assistance, Needs, and Resources (Tweet Count = 73,924, 32.1%)			
Topic	**Count**	**Terms**	**Representative Tweet**
OLIO food sharing app	21392	free, foodwaste, meat, recipe, fresh, gluten, bread, delicious, chicken, pizza, milk, fish, fruit, zerowaste, roll, egg, sweet, comfort, sandwich, fry, grain, sugar, organic, cheese, vegetable, chip, veggie, ingredient, soup, tasty	"Bagels plain 5 pack 14 april donated by Tesco " in #London #United-Kingdom https://t.co/2KitI4TQ4w #foodwaste #free
Food pantries	14987	family, donate, support, local, pantry, bank, community, distribution, provide, donation, volunteer, drive, student, distribute, box, serve, team, visit, partner, item, member, neighbor, charity, meal, church, collect, resource, resident, continue, share	Mobile Pantry through Arlington Charities with limited amount of food for Arlington ISD families Saturday 3/28. Registration required: https://t.co/B02UiYfjzv Hopscotch has been forced to change our method of food distribution to the students and families we help. We set up a central location at Jefferson High School on Commercial St. Donations: https://t.co/Fi6liXZ7Hs Daveâ©¤ï¸© https://t.co/h4n2l6HT7r

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Government assistance	11491	assistance, stamp, program, government, housing, state, cut, vote, provide, receive, benefit, trump, fund, include, relief, public, unemployment, access, healthcare, education, tax, service, wic, financial, apply, taxis, basic, law, cash, welfare	@borieholtz Social programs such as housing assistance, and food assistance have worked in the US to ease the worry of those that use them. Socialized Medicine would ease yet another burden from families that choose to pay for utilities over urgent medical care. #SocializedMedicineOrWhat "@FeedingAmerica estimates at least 30% of those with food insecurity nationwide aren't eligible for #SNAP. In some states, it's nearly 50%. Tightening eligibility...as new work requirements would do, would only increase that number." - @UpshotNYT https://t.co/7Ky7VZ8sB5 @kabobulator @MSNBC @maddow Guarentee if government would stop taxing the hell out of farmers on everything maybe they wouldnt need assistance. Also let the ones who can having fracking done on their property have it done. But once again they pay taxes. People on food stamps, unemployment do not
Food systems	11247	security, grow, system, create, market, farmer, produce, world, farm, build, industry, product, plant, base, nutrition, important, source, future, energy, land, production, change, solution, ensure, protect, focus, resource, safety, global, human	To keep people safe & prevent spread of coronavirus, we have closed the state's borders. We recognise the critical need to keep our primary industries sector moving & that's why there will be exemptions for food & commercial supply chains. Together, we will get through this. https://t.co/Uo3iDEF9SR How do we approach complex issues like food insecurity & weak #foodsystems? Through coordination & coherence. Join us on Oct 13 to hear from partners, experts & donors on how we can effectively #InvestFarmtoFork. #fundGAFSP https://t.co/mlZnjZPkqT
Pet food	8815	food, buy, feed, store, dog, grocery, learn, animal, bag, open, sell, shop, cat, drop, list, item, add, online, fill, treat, purchase, pet, step, door, expensive, link, shopping, dry, accept, check	Looking for ways to help a family in need this year?! Look no further! We've partnered with Don't Forget to Feed Me this month in order to collect unopened bags of dog and cat food for families, and pets, in need! You can learn more about them https://t.co/AAQQntCQtO

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Food banks	5992	food, week, bank, run, check, hear, test, hold, part, find, case, meet, guess, card, pass, turn, large, expect, group, point, half, amount, area, type, begin, quarantine, note, comment, pre, immediately	New Jersey food banks to receive $20 million to meet need in unprecedented time – WHYY https://t.co/goL26CUGQV Disappointed in how regular the food bank potatoes are this week.

II. Emergency Preparedness and Response (Tweet Count = 72,783, 30.7%)

Topic	**Count**	**Terms**	**Representative Tweet**
Tigray - aid	15082	people, aid, die, tigray, supply, starve, medicine, million, kill, world, end, emergency, force, humanitarian, access, medical, reach, continue, thousand, tigraygenocide, war, act, action, suffer, block, hunger, fight, situation, crisis, truck	@SenWarren It's inhuman, if not a daylight Genocide to close banks throughout the state indefinitely. Please tell @AbiyAhmedAli, open these banks so that people can at least buy food. #StopWarOnTigray #IAmTigraian https://t.co/6HWLRCyykn @GlobalGsts @WHO @DrTedros @OCHA_Ethiopia @GlobalFund @WFP @gavi @ICRC @ICRC_Africa @ifrc @IFRCAfrica @UNDP @UNICEF @UNICEFEthiopia @AfricaCDC Please help the Tigrians with basic humanitarian assistance, such as food water and medicine. Politics will never end.
Individual financial crisis	12561	money, pay, buy, job, rent, month, put, lose, spend, family, bill, table, struggle, afford, car, raise, gas, save, clothe, cost, work, account, cover, live, dollar, med, utility, due, son, cash	@CebuPacificAir please work on our refunds people need the money back for food, bills. Please So earlier this year we lost our food stamps. During the pandemic the food pantry has been stretched thin so we get less food, they just revoked our 120 dollar a month utility voucher and now we have been notified section 8 will no longer cover the total rent.

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Food insecurity crisis	10787	insecurity, covid, crisis, pandemic, high, issue, price, due, face, increase, low, shortage, number, experience, hunger, country, economy, address, report, fight, demand, level, rise, death, lockdown, lead, year, affect, risk, impact	@chantalp_MD Haven't personally had covid so take this with a grain of salt- what I'm gathering is that many people seem to be struggling with food/housing insecurity, so anything that could alleviate that? As unfortunate as it is, mental health resources are often seen as a luxury ðŸ˜“ Nearly one in four New Yorkers face food insecurity. Community fridges aim to assuage the problem. https://t.co/3PT9THbkoI
Family needs	9672	people, child, care, kid, school, health, poor, shelter, live, vaccine, country, homeless, parent, feed, black, rich, fact, person, sign, poverty, young, age, street, adult, white, deserve, promise, teach, education, matter	@Steve54712762 @Casper10666 Children at my child's school get free school meals for the first 3 years and that's great. After that you have to pay or packed lunch. This is when the issues start I have teacher friends who take extra food in for certain pupils. The fact they need to do that is wrong. @Mulachi1 @natalie_allison Kids learn better and behave better with some food in them. Providing the hungry with food is also in the best interest of public health: fed kids get sick less.
Essential services	9170	work, covid, home, fast, line, restaurant, hour, worker, long, stay, service, wait, close, place, business, essential, open, stand, safe, staff, hospital, employee, company, customer, job, sick, shut, folk, serve, dead	Our Ashtabula WIC clinic will be closed the rest of the week (Wednesday, July 29th-Friday, July 31st). Jefferson WIC is open on Friday. Stay tuned for updates. #AshtabulaWIC https://t.co/C9V1YaNlBx On July 23, 2020, PBC issued two COVID-19 Emergency Orders that clarify restrictions on the operating hours of restaurants, food establishments & other businesses, & extend the countywide facial coverings directive. More here: https://t.co/qHnrrVlp3C https://t.co/yeJAt4swhw https://t.co/C9V1YaNlBx

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Advice for emergency preparedness	8421	food, water, emergency, supply, clean, pack, city, hot, extra, top, prepare, power, fire, travel, include, cold, area, light, fall, ready, safe, heat, warm, air, side, stock, basic, hotel, electricity, plenty	Stay safe, prepare well - get water supplies, canned food, torches, batteries, first aid, masks if you can. This will get MUCH worse for a while but wont be for ever. #StayHome #staysafe #pvfc #Covid_19 #lockdownuk #TrumptheWorstPresidentEVER #Masks4All #2metresnotenough https://t.co/KvjMJi2QnF Groceries are being delivered to people at home , by the police force and local sheriffs , free sanitizers and food packs by the streets ... Los Angeles got me feeling all teary , Nigeria what's up
Values	7090	food, people, thing, life, lot, live, hard, problem, happen, work, understand, reason, time, survive, mind, agree, choose, human, point, worry, fix, write, real, kind, nee, absolutely, drug, hit, daily, mother	In times so continuous, it is the simple things that matter. Food on the grill for the family and Kaleo Radio playing on Pandora. Its time to relax and feel blessed for what we have. #Texas #Texit #Txlege #COVID #memories https://t.co/m61PWvQwz2 @FrothyFatCoffee @thisismylifeUSA @ChesseCorfe @GfyGood @TSowell4prez @WesPDX86 @alex_gorell @Vedantthelegend @DavidMo50860521 @AJS77 @_SalmanAnwar I haven't checked prices in years because I haven't had an urgent need, but even if that is true $40 is a lot of money when you're making choices between food or utilities and a dental checkup. But, I guess it's easier to say everything is a lie than accept our system is broken. also really need to work on my attention span more -keep forgetting if I fed cats -keep accidentally almost taking daily vitamins with every meal -keep messing up order of things when making food, like tossing a knife in the sink before I actually cut something with it

III. Mental and Physical Health (Tweet Count = 37,432, 15.8%)

Topic	Count	Terms	Representative Tweet

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Well-being/ nutrition	13077	eat, feel, hungry, healthy, stop, shit, nee, bad, body, fuck, food, literally, ass, hate, diet, fat, junk, fucking, sick, fast, hurt, bitch, stomach, exercise, brain, mouth, everyday, normal, pain, weight	@Lyricoldrap It's as real as you need it to be, in order to be motivated. Baby steps, for me it was drinking more water, getting active in doing things I enjoyed and eating more healthy. Moderation and phasing out of bad for you things. I get it, "food was all we had" but you have a daughter. It's #SugarAwarenessWeek. Time to appreciate just how artificially complex and nutritionally irrational some healthy eating guidelines can be..... this from https://t.co/O3fyA2HgN2 demonstrates. nb 'free sugars' refer to added sugar, rather than naturally occurring within a food https://t.co/ExJygfjAsJ
Food as self-medication	9141	food, day, today, meal, friend, time, dinner, nee, share, mom, lunch, forget, hope, bring, snack, worth, start, full, summer, cry, sad, morning, breakfast, finally, single, picture, update, remember, doctor, amazing	Okay, I just need to start on some food. That might help distract me from whatever this day is throwing at me.
Food as love	9082	food, give, love, man, talk, bad, baby, woman, post, follow, girl, make, fine, date, tweet, imagine, stress, thought, listen, mad, complain, photo, desperately, app, basically, hungry, hell, pic, dream, dude	@CielPha52115605 "I'll always be here love" no matter what they go through, he will always be there to give her hugs and buy her food when shes hungry, let her rest when shes tired
Recommendations	6132	food, time, year, start, great, big, plan, small, change, offer, set, end, deal, waste, story, full, move, space, part, learn, business, piece, class, town, goal, short, visit, large, avoid, ship	@streets @thewhicha @ScooterRiderFMX @InsulateLove Â£90 from dyas -don't get the expensive one unless u can afford it -you don't need to plan -you put the ingredients in the night before -set the timer and come home to delicious healthy food kept warm and sealed on slow cook for hrs @INTPangel And a biiiiig yes to large portions. The portions my great aunt cooks is massive. She always has food going or out and wants to feed everybody. Nobody will ever go hungry in her house. Lol

IV. Stay-At-Home Life (Tweet Count = 31,823, 13.4%)

Topic	Count	Terms	Representative Tweet

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Hunger (general)	13117	eat, feel, hungry, healthy, stop, shit, nee, bad, body, fuck, food, literally, ass, hate, diet, fat, junk, fucking, sick, fast, hurt, bitch, stomach, exercise, brain, mouth, everyday, normal, pain, weight	@Lyricoldrap It's as real as you need it to be, in order to be motivated. Baby steps, for me it was drinking more water, getting active in doing things I enjoyed and eating more healthy. Moderation and phasing out of bad for you things. I get it, "food was all we had" but you have a daughter. It's #SugarAwarenessWeek. Time to appreciate just how artificially complex and nutritionally irrational some healthy eating guidelines can be..... this from https://t.co/O3fyA2HgN2 demonstrates. nb 'free sugars' refer to added sugar, rather than naturally occurring within a food https://t.co/ExJygfjAsJ
Home food delivery	9395	food, order, call, delivery, send, stop, deliver, place, guy, pick, read, chinese, mask, wrong, person, lie, steal, question, spread, virus, word, doordash, tip, phone, driver, contact, speak, catch, answer, touch	I'm cold. I'm tired. I'm hungry. Therefore cuddles, a movie and some food delivery sound like a perfect date rn.
Daily Eating Habits	9311	food, back, leave, bring, hand, nee, put, love, sit, stuff, sleep, break, walk, house, home, happy, rest, room, head, ill, nice, throw, bit, bed, heart, car, wake, fridge, boy, move	we're getting food delivered for lunch...so guess who isn't leaving the bed till then .....fck i still need my coffee @BTS_twt https://t.co/xq2KwiQ3EG

V. Entertainment (Tweet Count = 21,145, 8.9%)

Topic	**Count**	**Terms**	**Representative Tweet**
Free drinks & entertainment	12102	free, drink, watch, show, night, win, tonight, enjoy, tomorrow, event, play, game, join, pm, great, video, book, late, truck, music, bar, fun, weekend, party, favorite, wine, season, beer, movie, gift	TACO TUESDAY AT SOHO LOUNGE ITS GOIN UPâ€¼ï¸◎ #FREEFOOD https://t.co/F4jZn7craX
Free/cheap food	9043	food, good, free, find, taste, real, nee, make, sound, chance, idea, true, thing, pretty, option, easy, stuff, cheap, click, remember, smell, super, mention, mexican, kind, twitter, brand, figure, news, spot	She defo let's guys take her on a date for free food Smells like broke over here https://t.co/JFEvEsfh4k anyone else thinks food tastes better when it's free?

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Figure 1: Twitter Metrics

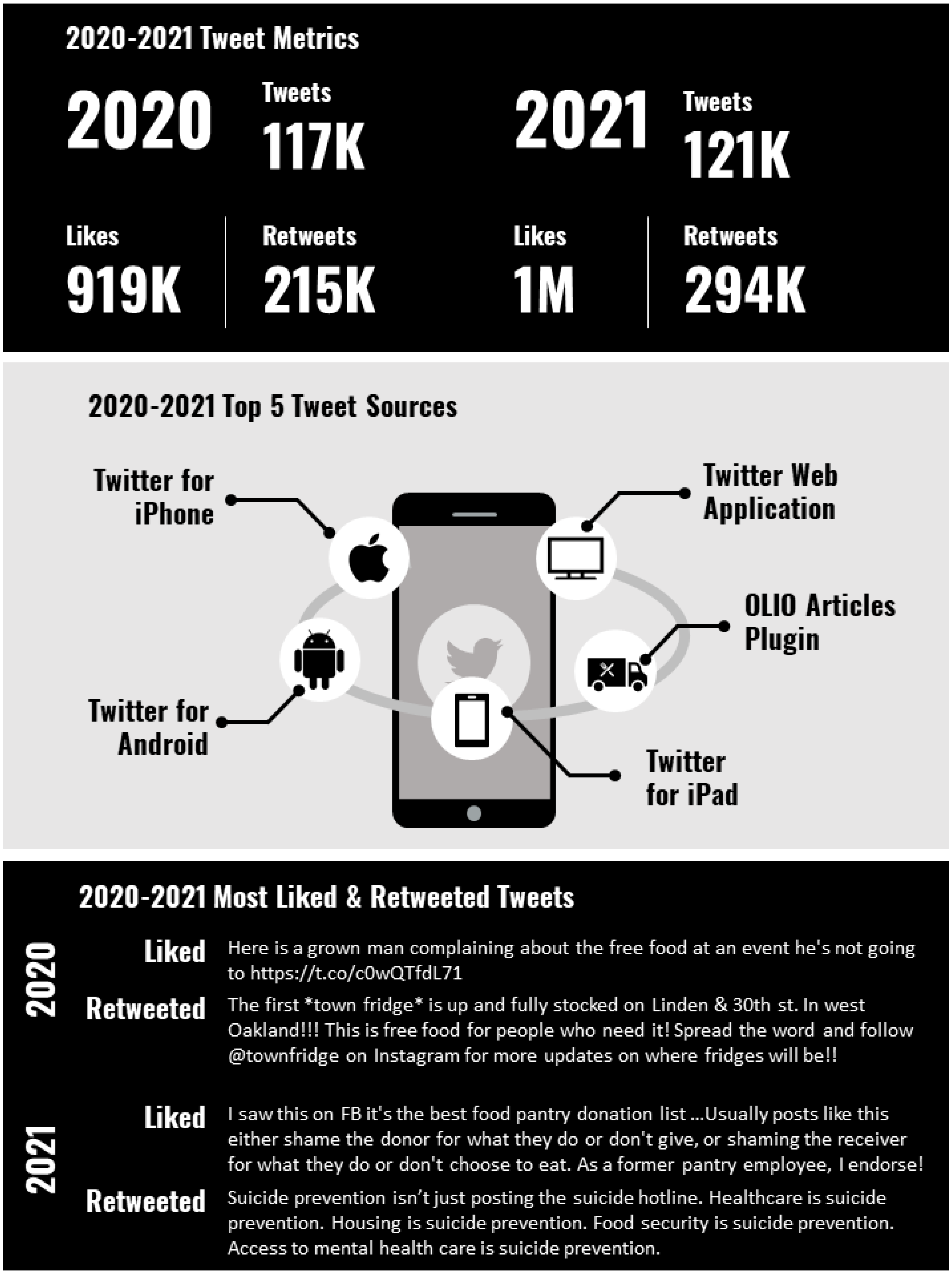

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Figure 2: Time Series Heatmap of Tweets Per Topic Per Day