Measuring and Analyzing Community Resilience During COVID-19 Using Social Media

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(ABSTRACT)

Community resilience (CR) has been studied as an indicator to measure how well a given community copes with a given disaster and provides policy directions on what aspects of the community should be improved with high priority. Although the impact of the COVID-19 has been serious all over the world and every aspect of our daily life, some countries have handled this disaster better than others. In this thesis, I aim to assess the effect of various news and Tweets collected during the COVID-19 pandemic on community functionality and resilience. First, we measure the community resilience (CR) in five different countries using Tweeter data and investigated how each country shows different trends of the CR, which is measured based on real or fake Tweets. We use Tweets generated in Australia (AUS), Singapore (SG), Republic of Korea (ROK), the United Kingdom (UK), and the United States (US) for Mar.-Nov. 2020 and measured the CR of each country and associated attributes for analyzing the overall trends. In the next step, we scrap and manually clean 4,952 full-text news articles from Jan. 2020 to Jun. 2021 and classify them into real, mixed, and fake news by fact-checking. Then we retrieve Tweets from 42,877,312 Tweets IDs from the same period and classify them into real, mixed, and fake Tweets using machine learning classifiers. We compare CR measured from news articles and Tweets based on three categories, namely, real, mixed, and fake. Based on the news articles and Tweets collected, we quantify CR based on two key factors, *community wellbeing* and *resource distribution*. We evaluate community wellbeing by assessing *mental wellbeing* and *physical wellbeing* while

evaluating resource distribution by assessing *economic resilience, infrastructural resilience, institutional resilience, and community capital*. Based on the estimates of these two factors, we quantify CR from both news articles and Tweets and analyze the extent to which CR measured from the news articles can reflect the actual state of CR measured from Tweets.

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(GENERAL AUDIENCE ABSTRACT)

The COVID-19 pandemic has severely harmed every aspect of our daily lives, resulting in a slew of social problems. It is critical to accurately assess the current state of community functionality and resilience under this pandemic to recover from it successfully. To accomplish this, various types of social sensing techniques, such as Tweeting and publicly released news, have been employed to understand individuals' and communities' thoughts, behaviors, and attitudes during the COVID-19 pandemic. However, some portions of the released news are fake and can easily mislead the community to respond improperly to disasters like COVID-19. In this thesis, I aim to assess the effect of various news and Tweets collected during the COVID-19 pandemic on community functionality and resilience. First, we measure the community resilience (CR) in five different countries, i.e., Australia (AUS), Singapore (SG), Republic of Korea (ROK), the United Kingdom (UK), and the United States (US), for Mar.-Nov. 2020 and measured the CR of each country and associated attributes for analyzing the overall trends. In the next step, we compare CR measured from news articles and Tweets based on three categories, namely, real, mixed, and fake. We quantify CR based on two key factors, *community wellbeing* and *resource distribution.* We evaluate community wellbeing by assessing *mental wellbeing* and *physical wellbeing* while evaluating resource distribution by assessing *economic resilience, infrastructural resilience, institutional resilience, and community capital.*

Dedication

I dedicate my thesis work to my family. A special feeling of gratitude to my loving parents, whose words of encouragement and push for tenacity ring in my ears.

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I would like to thank my supervisor, Dr. Jin-Hee Cho, for her dedicated support and guidance. Dr. Cho continuously provided encouragement and was always willing and enthusiastic to assist in any way she could throughout the research project.

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Urban Computing, Virginia Tech

To conclude, I cannot forget to thank my family and friends for all the unconditional support in this very intense academic year.

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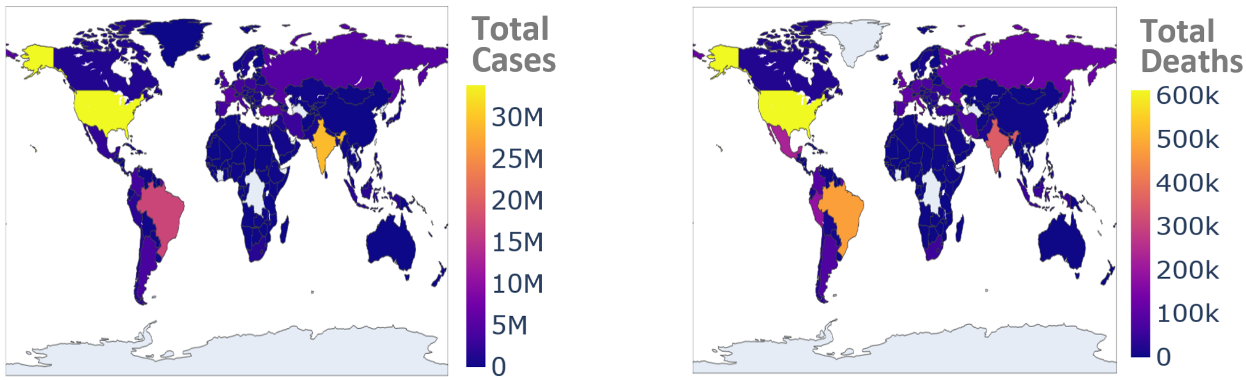
Chapter 1

Introduction

Emergency preparedness is critical for each society or country to surviving and recovering from unexpected disasters and minimizing human and economic losses. The degree of community resilience (CR) has been used as one of the key indicators representing how quickly a society can recover from disasters and how well the society functions even under the adverse effect of the disaster. The recent outbreak of COVID-19 has disrupted every aspect of our daily lives. To absorb and adapt against COVID-19 in an agile manner and quickly recover from it, maintaining a healthy, socially connected, and prepared community is critical [2, 3]. Community wellbeing is an essential asset to build a resilient community [4]. In addition, how resources are distributed in a community can present the community's resilience against a disaster like COVID-19. High accessibility to resources and their fair distribution is the keys to community resilience [5, 6, 7]. To measure the CR, first, we need a way of social sensing to collect community feedback for data analysis. Various social sensing methods have been used, such as online surveys, data analysis of social media information, or online trend analysis [8, 9, 10]. Second, we need meaningful metrics to estimate the CR using the collected data in terms of the core attributes of the CR. Although numerous studies have been conducted to examine how people have responded, recovered from, or been resilient against the COVID-19, the majority of existing research has been limited to online survey-based studies with small sizes of samples.



(a) Total infection cases (b) Total death cases

Figure 1.1: World COVID-19 total infection and death cases [1].

1.1 COVID-19 Across the World

Naturally, numerous studies have been studied to address diverse COVID-19 related problems in social sciences, epidemiology, computational sciences, or medical sciences [11, 12]. The COVID-19 has resulted in many losses in various areas, such as human deaths, economic losses, and health problems in the majority of countries in the world. As shown in Fig. 1.1, the US, Brazil, and India all have a high rate of COVID-19 infection and death. Various countries have responded differently to the pandemic based on different demographics, policies, public funding, management, international assistance, and preparedness, to name a few.

During the COVID-19, the various survey-based studies include assessing psychological resilience (e.g., anxiety, depression, and stress) and quality of life in China [13, 14, 15], examining neuroscientific impacts (e.g., physical, social, and psychological) and emotional responses in the United Kingdom [16, 17], and investigating socioeconomic resilience (e.g., ingenuity, empathy, and moral responsibility) in the US [18]. However, the sizes of samples were relatively small, and the samples were often biased. In addition, the information collected is limited to only questions answered. Further, conducting a fairly valid experiment is highly costly and time-consuming. On the other hand, social media can provide more realistic, rich information that can reflect the quality of people's real lives during a disaster.

1.2 Effect of Fake News on Community Resilience

Unfortunately, fake news may negatively impact maintaining community wellbeing and equitable resource distribution during COVID-19. The Internet, social media, and mass media platforms have generated a large volume of information flow during the COVID-19. Part of the information volume spreads false information (e.g., misinformation or disinformation), rumors, fake news, or hoaxes [19, 20]. Fake news is usually observed as more novel than real news; in addition, it flows on social/mass media noticeably faster, farther, and more broadly than real news [21]. In particular, emotion is a well-known appealing point that can easily provoke people's adverse feelings (e.g., false fears) and control their minds to act towards a specific behavior [22]. Fake news has been commonly used to manipulate and propagate false information by appealing to users' ideological perspectives, emotions, and desires to spread their views to other people [23]. Hence, spreading fake news in social/mass media can influence people's social behavior and impact community resilience by resource distribution and community functionality. However, prior studies have rarely investigated the effect of fake news on community resilience. Most existing research works that have been conducted are online surveys based on responses from small populations [13, 18, 24]. Furthermore, little research has been conducted to assess community resilience via social media.

1.3 Key Contributions

We made the following **key contributions** in this work:

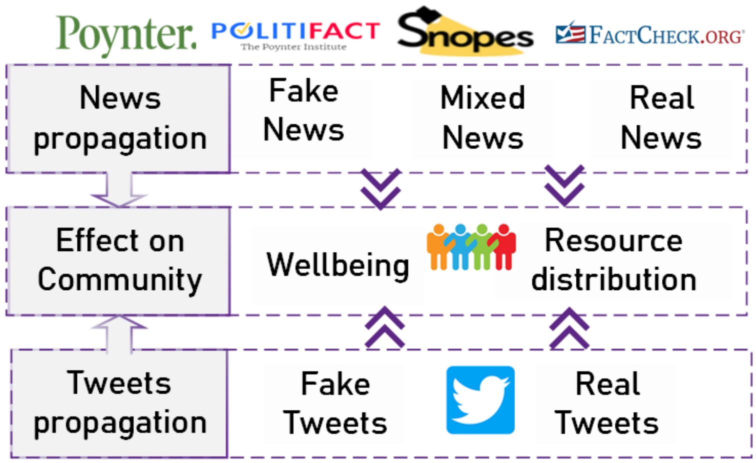


Figure 1.2: The effect of various types of news/Tweets on community

1. No prior work has estimated community resilience based on community wellbeing and resource distribution using social media (i.e., real and fake). This is the first work that proposed a novel CR metric using these two attributes captured based on social media information. This metric is generic and applicable to measure CR during any disaster.

2. No prior work has proposed the metrics of community resilience based on news articles (i.e., real, mixed, and fake). To the best of our knowledge, the effect of fake news on CR has been rarely studied. This is the first work that analyzes the effect of fake, mixed, and real news on community wellbeing, economic resilience, infrastructure resilience, instructional resilience, and community capital. We develop a novel CR metric to investigate these effects.

3. We presented a novel method to assess CR by leveraging linguistic and psychological patterns as well as natural language processing (NLP) tools. Although sentiment analysis has been conducted for measuring mental health during the COVID-19, there has been no metric defined to capture the CR of multiple countries using social media. No comparison of sentiment analysis under multiple countries has been conducted to investigate the different behavioral patterns of dealing with disasters in the literature. To the best of

our knowledge, we are the first to measure CR using real and fake Tweets based on the proposed CR metric and analyzing its trends in different countries.

4. We conducted an extensive comparative analysis of CR measured by Tweets under the five countries, including Australia (AUS), Singapore (SG), Republic of Korea (ROK or South Korea), the United Kingdom (UK), and the United States (US). Further, we discussed how each country's CR is different under both real and fake news and what the difference implies in handling the disaster.

5. We examined the linear and monotonic correlations between fake and real Tweets in terms of the measured CR and its attributes. That is, we investigated how similar CR is shown when it is measured using fake and real Tweets. To increase the validity of this relationship, we used two correlation coefficients, Person and Spearman, and demonstrate the relationship of CRs between real and fake Tweets. In addition, we examined how this trend is different depending on each country when investigating the measured CRs of the five countries.

6. This work is the first to use news articles and Twitter to assess community resilience during the COVID-19. We use fact-checking to collect 4,952 full-text news articles and categorize them as real, mixed, or fake news. In addition, we retrieve Tweets from 42,877,312 Tweets IDs from Jan. 2020 to Jun. 2021. We compare the measures of CR from the data, including news and Tweets.

7. We analyze the correlation between measurements of CR attributes by each type of news (i.e., real, mixed, or fake) and Tweets (i.e., real or fake). From this analysis, fake news is shown influencing people's behaviors towards undesirable states, undermining CR in reality. Moreover, the CR measured based on real or mixed news articles can reflect actual states of the CR measured from Tweets.

8. We conduct a resilience analysis of various types of news (i.e., real, mixed, or fake) and Tweets (i.e., real and fake) via an output-oriented analysis to show the values of each CR attribute over time, as well as a capacity-based analysis to demonstrate the time-averaged CR measurements. We also conduct statistical analyses to examine the correlation of CR attributes measured from news and Tweets.

1.4 Publications

From this master thesis research, we generated the following two publications [25, 26]:

- Jaber Valinejad, Jin-Hee Cho, "Measuring and Analyzing Community Resilience During the COVID-19 Through Social Media: Comparative Study of Five Countries," Submitted to *IEEE Transactions on Computational Social Systems*, Jun. 2021. (Under Review) [25]

- Jaber Valinejad, Zhen Guo, Jin-Hee Cho, and Ing-Ray Chen, "Measuring Community Resilience During the COVID-19 based on Community Wellbeing and Resource Distribution," Submitted to *IEEE Transactions on Big Data*, Sep. 2021. (Under Review) [26]

1.5 Author's Background

I was involved in various programs as a multidisciplinary person, including computer science, disaster resilience and risk management, electrical and computer engineering, industrial engineering, and urban computing. I am currently researching resilience in Cyber-Physical-Social Systems, focusing on critical infrastructure and social science aspects. I've worked on a variety of multidisciplinary projects and have papers published in a variety of conferences and journals. Specifically, my work focuses on community resilience [27, 28, 29], urban computing [30, 31, 32, 33], critical infrastructures [34, 35, 36, 37, 38], social network [29, 30, 31], and Energy [30, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49].

1.6 Thesis Outline

This thesis is organized as follows:

- Chapter 2 provides the literature review on metrics of community resilience, sentiment analysis using social media information, fake news research, and limitations and gaps of the existing approaches.

- Chapter 3 discusses measuring and analyzing community resilience during the COVID-19 through social media for five countries, including Australia, Singapore, the Republic of Korea (also known as South Korea), the United Kingdom, and the United States. This chapter first presents community resilience metrics, including community well-being and community capital. Then, it provides a discussion on the procedures of measuring community resilience via social media information. The procedures consist of collecting COVID-19-related Tweets, classifying all Tweets as real, mixed, or fake based on three ML classifiers, identifying physical-psycho-social states and behavioral patterns using LIWC, and measuring CR based on the extent of exhibiting the considered LIWC features. Afterward, this chapter provides numerical results and analyses.

- Chapter 4 provides a discussion on how to measure community resilience during the COVID-19 based on community wellbeing and resource distribution. Then, it provides the procedures for measuring CR via social media information. This process includes collecting news using web-scraping, classifying news articles, processing news articles for analysis, collecting COVID-19-related Tweets, classifying all Tweets as real or fake, and identifying the physical-psycho-social states and behavioral patterns using LIWC. Afterward, it provides numerical results and analyses on the news, mental and physical wellbeing, output-oriented resilience, capacity-based resilience, statistics of news, and Tweets.

- The conclusion to the two frameworks presented in Chapters 3 and 4 are provided in Chapter 5. It concludes with a discussion of community resilience.

Chapter 2

Literature Review

In this chapter, we discuss how community resilience has been defined and quantified in the literature. In addition, we give a brief overview of sentiment analysis research on COVID-19 using social media datasets.

2.1 Community Resilience

Community resilience (CR) is defined as the capacity of a community to absorb the shock caused by a specific class of disaster, recover from this event, and return to normal functionality [27]. Note that community functionality is how well a community function to provide a variety of vital services to its community residents [29]. This process includes how a social system absorbs the impact of the stress and copes with threats, as well as how to adapt to post-event situations by reorganizing, changing, and/or learning to handle the threat from the disasters. This definition is well aligned with the general concept of 'resilience,' which embraces a system's fault tolerance (i.e., functioning under threats or errors), adaptability (i.e., adapting to disruptions), and recoverability (i.e., recovering quickly from the disrupted situations) [50].

CR has been measured based on various types of indicators, indices, or metrics. The common CR indicators include the Baseline Resilience Indicators for Communities (BRIC) [51], COmposite of Post-Event WELLbeing (COPEWELL) [52], United Nations Office for Disaster Risk Reduction (UNDRR) [53, 54], Disaster Resilience Of Place (DROP) [55], Community Disaster Resilience Index (CDRI) [56], Resilience Capacity Index (RCI) [57], and Resilience Analysis and Planning Tool (RAPT) provided by the Federal Emergency Management Agency (FEMA) [58, 59]. Even though CR has been measured differently in the past in response to various disasters, it has primarily been measured based on social wellbeing, economic functionality, institutional functionality, infrastructure functionality, community capital functionality, and ecological functionality [51, 60].

Springgate et al. [61] proposed the *wellbeing theory* discussing a measure of community wellbeing in terms of positive emotions, engagement, relationships, meaning, and accomplishment. Ruzek [2] discussed 'health' in terms of behavioral, physical, social, and environmental wellbeing. Higher psychological wellbeing can introduce higher sustainability, equality, resilience, and inclusion [2, 61, 62]. The key factors impacting people's resilience to disasters were also studied, such as family distress, available support systems, disruption of school/job programs, or loss of loved ones/property [63].

The distribution state of physical and social resources is another indicator of community resilience. Physical resources consist of critical infrastructures, electricity, water, food, medicine, emergency services capacity, transit capacity, grocery, pharmacy, or workplaces. Social resources include community capital and institutional resources [64], which allow people to interact with other people for their social activities. During the COVID-19, we observed aggressive panic buying behaviors of food, toilet papers, and sanitary products across the country in Singapore [65], Hong Kong [66], and China [67]. This is known to reduce community resilience due to a lack of balanced resource distribution.

2.2 Sentiment Analysis Using Social Media Information

Social media information has been used to conduct sentiment analysis to investigate the impact of disasters or events on people's mental health. People's mental health has been measured based on emotions extracted from social media information where the languages used in social media have been analyzed by machine learning (ML) or natural language processing (NLP) techniques [68, 69]. Coppersmith et al. [68] leveraged the linguistic inquiry and word count (LIWC) to present an analysis of mental health phenomena in publicly available Twitter data. They showed how the thoughtful application of simple NLP methods could provide insights into specific mental disorders and health. Molyneaux et al. [69] examined the relationship between social networking sites and CR using a survey of Internet users.

Li et al. [70] analyzed emotions and psychological states extracted from the datasets of Weibo users using the LIWC [71, 72]. Hou et al. [73] examined risk perception, negative emotions (e.g., sadness, anger, anxiety), and behavioral response (e.g., panic buying) to the COVID-19 from the datasets of Sina Weibo, Baidu search engine, and Ali e-commerce marketplace using the LIWC. They also analyzed misinformation and rumors on the COVID-19 and found its relationships with aggressive panic buying behaviors. Additionally, Naseem et al. [74] analyzed attitudes toward the COVID-19 by focusing on individuals who interact with and share social media on Twitter in order to ascertain positive and negative sentiments.

2.3 Community Resilience and Fake News

Social media activities influence community resilience [12] in terms of social wellbeing and community capital. Official and informal sources use social media to inform information to handle a disaster for public safety, such as social distance, sanitation, food or transportation availability, or business hours. In addition, social media provide good networking tools to engage people with a community or government guidance [75]. However, false information has been often propagated through social media, such as fake news or rumors, which can easily amplify fear, anxiety [65, 76], outright racism, disgust, and mistrust [66]. These unnecessary misperception has been the key to trigger irrational, undesirable responses to disasters. In the literature, people's responses and behaviors to the COVID-19 have been measured by analyzing social media information. The examples include emotions and psychological states extracted from the datasets of Weibo users using the linguistic inquiry, word count (LIWC) framework [70, 71], risk perception, negative emotions (e.g., sadness, anger, anxiety), and behavioral responses (e.g., panic buying) to COVID-19 from the dataset of Sina Weibo, Baidu search engine, and Ali e-commerce marketplace using LIWC [73]. Aggressive panic buying behaviors were more prominently observed when more misinformation or rumors on the COVID-19 were disseminated [73]. Emotions (e.g., surprise, disgust, fear, anger, sadness, anticipation, joy, and trust) in replies were also captured from real and false Tweets using the National Research Council Canada (NRC) [77] and LIWC [21]. Ju et al.[78] measured people's mental health based on emotions extracted from social media data, which was analyzed using machine learning (ML) or NLP techniques [68, 69]. Dictionary-based sentiment analysis tools have been used to capture emotions, such as leading lexicons provided by National Research Council Canada (NRC) [77], sentiment analysis and cognition engine (SEANCE) [79, 80], the linguistic inquiry, and word count framework (LIWC) [71, 72], WordNet [81, 82, 83], and expressions of opinions and emotions in the language (MPQA) [84, 85]. In addition, learning task-specific emotion using neural networks has been analyzed the emotional states of information, news, and users [86, 87]. Social media's main benefits during the disaster are connecting easily with more people and quickly informing an early warning or supportive information for risk mitigation and fast response and recovery [88]. However, the adverse impact of social media is also well-known, such as propagating false information (e.g., fake news or rumors) that amplify fear, anxiety [65, 76], outright racism, disgust, and mistrust [66]. Thanks to a large volume of social media data available, researchers have investigated the impact of COVID-19 on people's mental health using social media information even during a short period of time.

2.4 Fake and True News Propagation

The first appendix provides the literature on information-processing behavior, risk perception, fake and true news propagation, and the effect of bias on community resilience.

2.5 Limitations and Gaps of the Existing Approaches

However, the works discussed above have not introduced the concept of CR based on community wellbeing and resource distribution using both social media news articles (i.e., real, mixed, and fake) and Tweets (i.e., real and fake) to compare their measurements and investigate their correlations. Further, no comparison of sentiment analysis under multiple countries has been conducted to investigate the different behavioral patterns of dealing with disasters in the literature. In this work, we fill these gaps.

Chapter 3

Measuring and Analyzing Community Resilience During the COVID-19 Through Social Media: Comparative Study of Five Countries

This chapter measures and analyzes community resilience in five countries: Australia, Singapore, the Republic of Korea (also known as South Korea), the United Kingdom, and the United States. This chapter is based on our submitted paper in [25].

3.1 Community Resilience (CR) Metrics

We measure CR with respect to the level of community functionality at time t. Fig. 3.1 describes how the community functionality, denoted by $CF(t)$, can be represented with respect to time t.

Throughout the remainder of the thesis, we will commonly utilize the words CR and community functionality (CF). CR and CF are two distinct metrics in that CR is used as a metric based on the time-averaged CF while CF is used as an instantaneous metric measuring CR

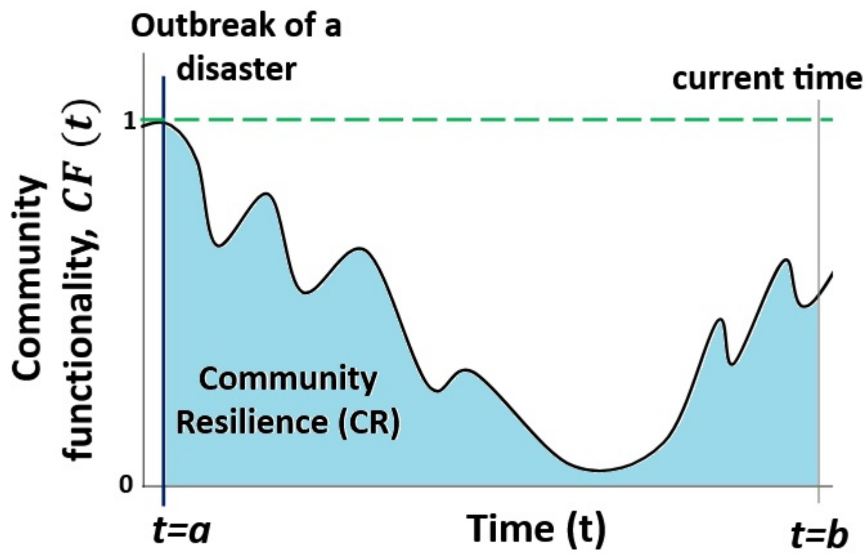


Figure 3.1: Measurement of community resilience (CR) based on community functionality $CF(t)$ during the period of $[a, b]$.

at time t.

The $CF(t)$ is estimated by considering both community wellbeing ($CW(t)$) and community capital ($CC(t)$) at time t. Hence, CR is measured by:

$$CR = \int_{t=a}^{b} CF(t)\, dt = \int_{t=a}^{b} \frac{CW(t) + CC(t)}{2}\, dt, \tag{3.1}$$

where $[a, b]$ is the time period considered to measure the CR. We consider CW and CC equally in this work. However, depending on the emphasis of CR in a given domain, CW and CC can be differently weighted. For the fair consideration of these two components, we normalized the measures of CW and CC to be real numbers ranged in $[0, 1]$ using min-max scaling [89]. Now we discuss the details of the two attributes, CW and CC, as follows.

Figure 3.2: The proposed community resilience metric consisting of community wellbeing and community capital.

3.1.1 Measuring Community Wellbeing (CW)

According to the World Health Organization (WHO) [90, 91], CW is defined based on three dimensions of wellbeing: mental wellbeing (MW), physical wellbeing (PW), and social wellbeing (SW). The CW is given by:

$$CW = \frac{MW(t) + PW(t) + SW(t)}{3}, \tag{3.2}$$

where each wellbeing component is considered equally. Again depending on a domain requirement, each dimension of wellbeing can be considered with a different weight. In this work, we weigh each component with an equal importance.

Now we describe how each dimension of the CW is measured by using NLP tools as follows:

- **Mental Wellbeing**: Negative emotional characteristics, such as anxiety, depression, and anger, have been known as the conventional symptoms of mental illnesses [8, 31, 92, 93]. We measure *anxiety, sadness*, and *anger*, which are in the categories of the LIWC, to represent the overall mental wellbeing of a given community.

- **Physical Wellbeing**: We consider the following features to measure the states of people's physical wellbeing:
  - *First-person singular pronounces*: According to the psychological study of language [94], the increased use of the first-person singular pronounces using the LIWC can imply physical pain and more attention to a self [94]. To reflect this, we used the LIWC category of 'first-person singular' to measure this language pattern.
  - *Words representing physical activities and health*: The extent of physical activities and health is measured based on the increased use of motion (e.g., 'arrive,' 'go,' 'car'), leisure (e.g., 'cook,' 'chat,' 'movie'), work-related (e.g., 'job,' 'majors,' 'xerox'), health-related (e.g., 'fitness,' 'healthiness,' or 'wellness'), and positive body-related terms (e.g., 'hands,' 'cheek,' and 'spit') terms [95, 96, 97, 98]. We measured these language patterns based on the degree of using terms under 'motion,' 'work,' 'leisure,' 'health,' and 'body,' in the categories of the LIWC.
- **Social Wellbeing**: People's responses to disasters are influenced by various social factors, such as family distress, available support systems, disruption of school/work programs, loss of loved ones/property, and the community's response to the disaster [11, 12]. Hence, we consider friend, family, and work-related words in the category of LIWC to measure social wellbeing. Each category is detailed as:
  - *Social*: Higher social wellbeing can be related to using more social terms in relationships with friends or religions in communication [99, 100].

  - *Family*: Higher social wellbeing is also related to the frequent use of more familial-related terms, which implies a greater sense of family-related wellbeing [101].
  - *Work*: Higher social wellbeing is sensed when individuals use more work-related terms, such as 'money,' 'achieve,' or 'reward' [102, 103].

3.1.2 Measuring Community Capital (CC)

We measure CC by using the LIWC as follows:

- **Community Cooperation**: We measure CC based on the language patterns representing community cooperation, which is captured by the following key attributes:
  - *Communication Efficiency*: The increased use of complex words and words with more than six letters is known as less efficient for communication, cooperation, and social interaction [30, 104]. To consider this, we measure the opposite degree of 'Words> 6 letter' in the category of the LIWC.
  - *Group-Oriented Communications*: The frequent use of the first person pronounce (e.g., 'we,' 'us,' 'our') indicates group-oriented interaction and cohesion [105]. Assent-related languages (e.g., 'agree,' 'OK,' 'yes') are known to promote group consensus, interaction, and cooperation in psychological linguistics [106]. Hence, we measured the frequency of words using the 'first-person plural' pronounces and 'assent' in the categories of the LIWC.
  - *Social Process-Related Communications*: Increasing the use of social process languages implies an increase in social interaction, engagement, and cooperation [107, 108]. We measured this by considering 'friend' and 'family' in the categories of the LIWC.

Note that more words under each category indicate a higher value under the category. Hence, we normalized the value of each attribute in CR by dividing the accumulated degree by the number of words for a fair comparison.

3.2 Procedures of Measuring CR via Social Media Information

To measure CR during the COVID-19 for Mar.-Nov. 2020 using real and fake Tweets, we took the following steps:

3.2.1 Collecting COVID-19-related Tweets

We used Twitter datasets to measure the CR during the COVID-19 under the following five countries: AUS, SG, ROK, UK, and the US. We investigated 80,000 Tweet IDs under each country during the period and collected approximately 50,000 Tweets for each country. The number of Tweets under the SG is 50,000, which is observed as the minimum among all five countries. For a fair comparison, we used 50,000 Tweets for all five countries. After removing non-English Tweets and shuffling, each country ends up with 42,000 Tweets. Finally, we made these Tweets ordered chronologically from Mar. to Dec. 2020.

3.2.2 Classifying all Tweets as real or fake based on three ML classifiers

In order to analyze the CR based on both real and fake Tweets, first we classified them in terms of real (or true) or fake. We leveraged eight existing ML classifiers and trained them

Table 3.1: Prediction Performance of Various Machine Learning Classifiers

ML Classifier	Accuracy	Precision	Recall	F-score
Passive Aggressive	0.995	0.995	0.995	0.995
Logistic Regression	0.984	0.984	0.984	0.984
Bagging Classifier	0.618	0.779	0.598	0.532
K-Neighbors	0.671	0.782	0.655	0.622
Decision Tree	0.994	0.994	0.994	0.994
Random Forest	0.519	0.623	0.5	0.346
AdaBoost	0.995	0.995	0.995	0.995
Multi Layer Perceptron	0.966	0.967	0.966	0.966

using the datasets in [109], which contain 23,481 fake Tweets and 21,417 real news articles. Based on the prediction performance of all eight ML algorithms, as shown in Table 3.1, we selected the top three ML algorithms, which are Passive-Aggressive, Decision Tree, and AdaBoost. Using these three ML algorithms, we predicted the truthfulness of each Tweet and determined the final prediction for each Tweet based on the majority rule of the three ML algorithms (i.e., at least 2 ML classifiers should give the same prediction result).

3.2.3 Identifying physical-psycho-social states and behavioral patterns using LIWC

We chose the LIWC as our text-mining tool in order to extract each country's response to COVID-19 because it can provide a rich volume of diverse physical-psycho-social features and behavioral patterns. Before analyzing Tweets using the LIWC, we ordered all Tweets monthly and cleaned datasets using various NLP tools (i.e., nltk, string, stopwords, RegexpTokenizer, regexp, WordNetLemmatizer, and PorterStemmer) for each country's fake and real Tweets. Specifically, we first removed HTML, punctuation, stop words, and word stammering. And then, we extracted all LIWC features considered to assess the CR.

Table 3.2: ATTRIBUTES OF CR AND LIWC FEATURES TO MEASURE THE CR

<table>
<tr><th colspan="2">Attribute of CR</th><th>Categories in the LIWC</th></tr>
<tr><th colspan="3">Community Wellbeing</th></tr>
<tr><td colspan="2">Mental wellbeing</td><td>Anxiety, sadness, anger, and word count</td></tr>
<tr><td colspan="2">Physical wellbeing</td><td>First-person singular, health, leisure, work, body, motion, and word count</td></tr>
<tr><td colspan="2">Social wellbeing</td><td>Religion, family, money, social, friend, achieve, reward, and word count</td></tr>
<tr><th colspan="3">Community Capital</th></tr>
<tr><td rowspan="3">Community cooperation</td><td>Intensive communications</td><td>Words> 6 letters and word count</td></tr>
<tr><td>Group-oriented communications</td><td>First-person plural, assent, and word count</td></tr>
<tr><td>Social process-related communications</td><td>Social,Family, friend, and word count</td></tr>
</table>

3.2.4 Measuring CR based on the extent of exhibiting the considered LIWC features

Now we measure CR based on all the LIWC features considered, as described in Table 3.2.

In order to better capture the dominant trends of the CR under each country using the Tweeter datasets, we used fitting curves to extract the trends of the measured CR under the five countries. To optimize the accuracy of the fitting curves, we examined multiple fitting functions and obtained the values of multiple goodness metrics, including Residual (R), Residual Sum of Squares (RSS), Total Sum of Squares (TSS), the coefficient of determination (R^2), and Adjusted R^2, denoted by R^2_A [110]. To be self-contained, I also summarized how each fitting function is presented and how each goodness metric is calculated in Table 3.3.

To provide the example goodness metrics for various fitting curves shown in Table 3.3 (as we observed similar values for other datasets used in our work), we generated goodness values

Table 3.3: Fitting Functions and Goodness Metrics

Distribution	Fitting function
Exponential	$a \times e^{-b \times x} + c$
Gaussian	$a_1 \times e^{-((x-b_1/c_1)^2} + a_2 \times e^{-((x-b_2)/c_2)^2}$
Polynomial	$p_1 \times x^2 + p_2 \times x + p_3$
Power	$a \times (x^b) + c$
Rational	$(p_1 \times x^2 + (p_2 \times x) + p_3)/(x^3 + q_1 \times x^2 + q_2 \times x + q_3)$
Sine	$a1 \times sin(b_1 \times x + c_1)$
Weibull	$a \times b \times (x^{b-1}) \times e^{-a \times (x^b)}$
Goodness	Metric function
R	$\sum \lvert y - \tilde{y} \rvert$
RSS	$\sum (y - \tilde{y})^2$
TSS	$\sum (y - \bar{y})^2)$
R^2	$1 - (RSS/TSS)$
R_A^2	$1 - ((RSS/(n - N^{var} - 1))/(TSS/(n-1)))$

Table 3.4: Goodness Measures Under Various Fitting Functions

Fitting function	R	RSS	TSS	R^2	R_A^2
Exponential	-	-	-	-	-
Gaussian	-	-	-	-	-
Polynomial	1.1789	0.2682	0.7551	0.6448	0.5940
Power	1.4900	0.3974	0.7551	0.4737	0.3985
Rational	-	-	-	-	-
Sine	4.3000	2.7412	0.7551	-2.6302	-3.1489
Weibull	3.4683	1.8233	0.7551	-1.4147	-1.7597

Note: Each value is rounded up to the four decimal places.

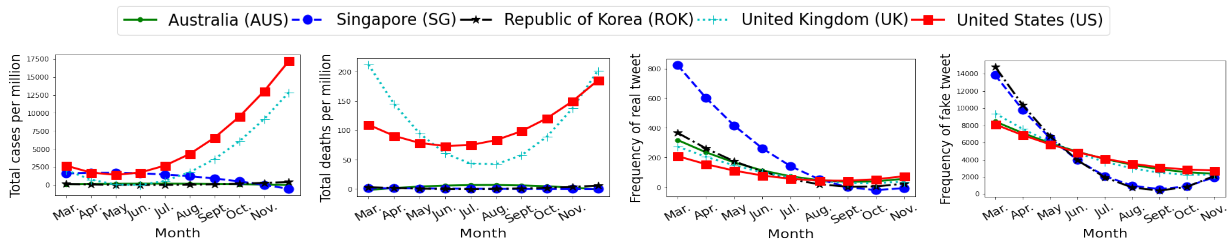
using the dataset on the community capital of fake Tweets in Table 3.4. For Exponential, Gaussian, and Rational functions, there is no optimal fitting curve. The polynomial function had the highest level in R^2 and R_A^2 while showing the lowest level in R and RSS. Therefore, we used the polynomial fitting function to analyze the trends of the measured CR along with measured CW and CC.

Next, we demonstrate the measured CR and its associated attributes under real and fake news of the five different countries, including the AUS, SG, ROK, UK, and US. We also discuss how the trends are different and the underlying reasons behind the observed trends.

3.3 Numerical Results & Analyses

3.3.1 Amounts of Real and Fake News

Fig. 3.3 displays the total numbers of the COVID-19 infection cases and deaths per million population and the frequencies of fake and real Tweets under the five countries (i.e., AUS, SG, ROK, UK, and the US) during the period of Mar.-Nov. 2020. It is noticeable that the US and UK had experienced substantially higher infection and death cases than the other three countries. In addition, SG showed even decreasing trends in both infection and death cases over time. Although during the summer (e.g., Jun.-Aug.), the death cases drop a little, they increase again going towards the winter seasons. Unlike the resurgence of infection and death cases in the UK and US, the amount of real and fake news keeps decreasing overall with a slight resurgence during the Oct./Nov. timeline. One interesting observation is that SG shows a substantially larger amount of real Tweets than other countries (see Fig. 3.3c). In addition, SG and ROK had substantially decreasing trends of fake Tweets, although they had even a larger amount of fake Tweets at the beginning of COVID-19 (e.g., Mar.-Apr.) than the other three countries. AUS also showed very similar trends in generating real and fake Tweets. However, AUS showed vastly different COVID-19 infection and death cases trends from the US and UK. This may be closely related to low population density, which inherently makes AUS advantageous in dealing with COVID-19. Hence, we believe that depending on each country's different environment, and strategies to handle COVID-19, fake or real news may also influence it differently.



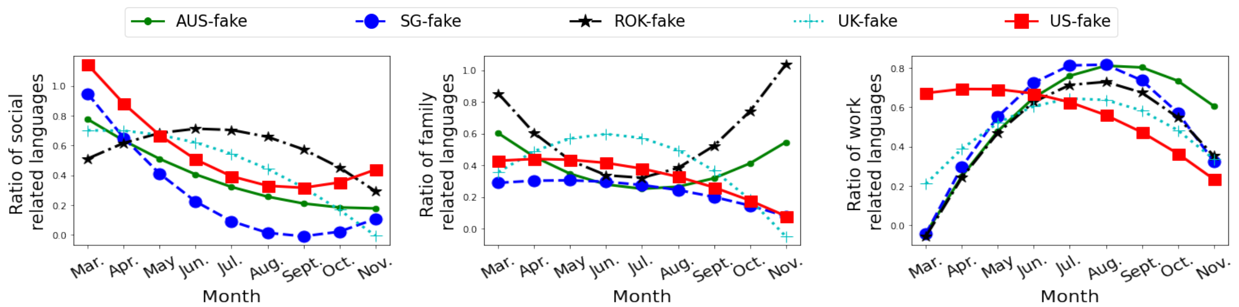
(a) Total infections per million (b) Total deaths per million (c) Frequency of real Tweets (d) Frequency of fake Tweets

Figure 3.3: Total numbers of infections per million, total numbers of deaths per million, the frequency of fake Tweets, and the frequency of real Tweets for the five countries during Mar.-Nov. 2020.

3.3.2 Social Wellbeing from Fake and Real Tweets

For the first framework, we defined CR in terms of a function of community wellbeing (CW) and capital (CC), where CW is measured based on mental, physical, and social wellbeing. In addition, we measured social wellbeing based on three language use patterns representing social life, family, and work. In this section, we demonstrate the three aspects of social wellbeing measured by real and fake Tweets and analyze the underlying implications. Fig. 3.4 shows the three dimensions of social wellbeing using real and fake Tweets under the five different countries during the Mar.-Nov. 2020.

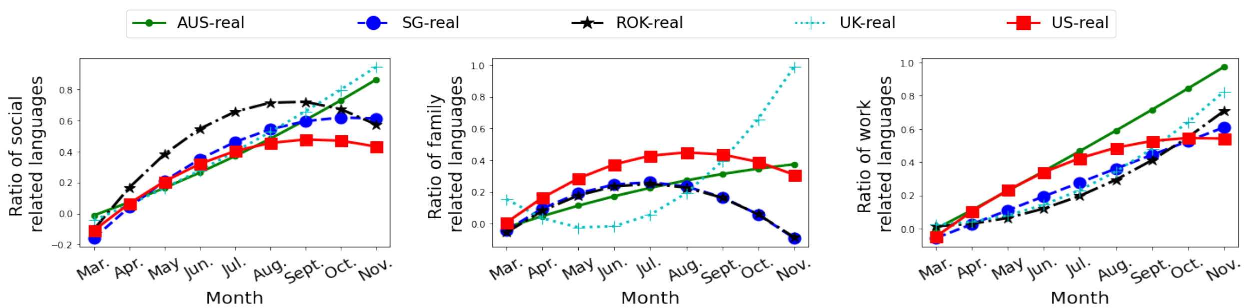
From Fig. 3.4, we noticed the following key trends: (1) In social life-related features, overall, we observe fake Tweets decrease while real Tweets increase over time. SG showed the lowest fake Tweets while maintaining a comparable level of real Tweets as other countries; (2) In family-related features, trends under different countries are unique in both real and fake Tweets because family-related topics may be culture-dependent, so not showing clear overall trends associated with how to handle the COVID-19 in each country; and (3) In work-related features, all countries show steadily increasing trends in real Tweets while reaching the peak during the summer and going down again in fake Tweets. In particular, the high ratio of real Tweets for work-related features in AUS and its increasing rate is impressive. This may



(a) Social features from fake Tweets.

(b) Family features from fake Tweets.

(c) Work features from fake Tweets.



(d) Social network features from real Tweets.

(e) Family features from real Tweets.

(f) Work features from real Tweets.

Figure 3.4: Measuring social wellbeing in terms of social, family, and work features in LIWC using real and fake Tweets for the five countries during the Mar.-Nov. 2020.

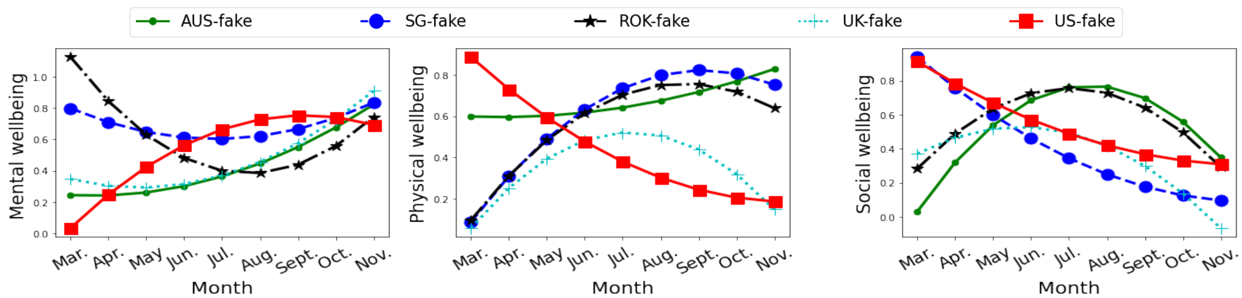
explain AUS's fast recovery from the COVID-19 compared to the other countries.

Overall, we can observe that social wellbeing in these three dimensions has shown an increase in real Tweets while fake Tweets deliver more pessimistic perspectives, representing a decrease in social wellbeing.

3.3.3 Community Wellbeing: Mental, Physical, and Social

Fig. 3.5 shows the three aspects of CR in terms of mental, physical, and social wellbeing under the five countries during the same period as before.

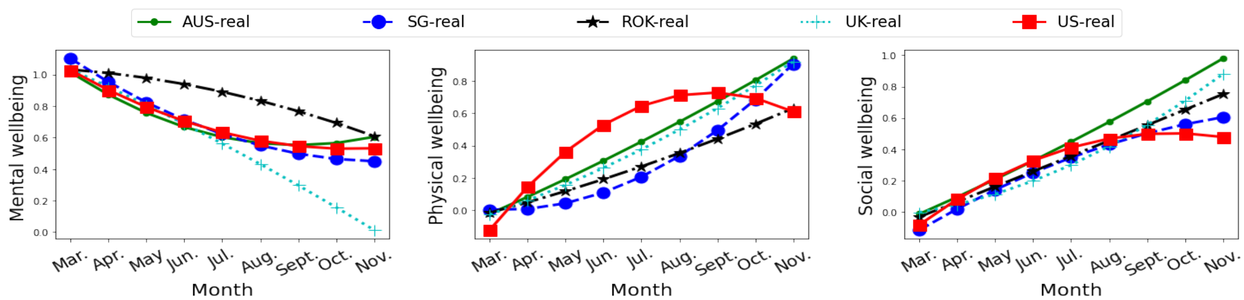
We found the following trends from Fig. 3.5: (1) Overall mental wellbeing (MW) measured by fake Tweets have increased over time while MW measured by real Tweets has decreased;



(a) Mental wellbeing from fake Tweets.

(b) Physical wellbeing from fake Tweets.

(c) Social wellbeing from fake Tweets.



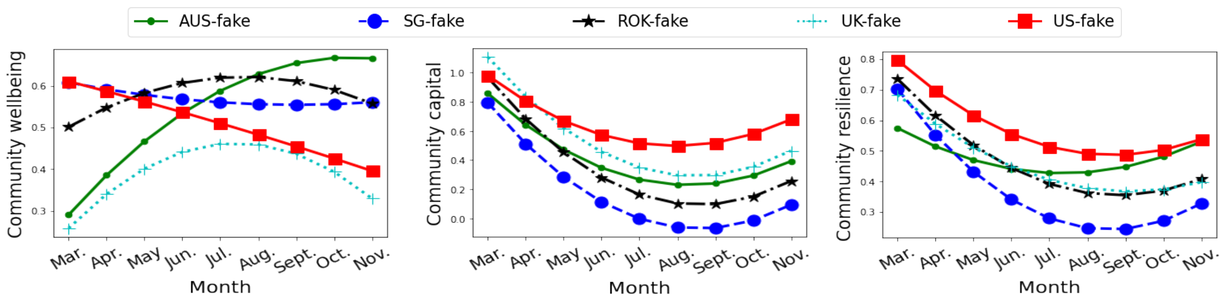
(d) Mental wellbeing from real Tweets.

(e) Physical wellbeing from real Tweets.

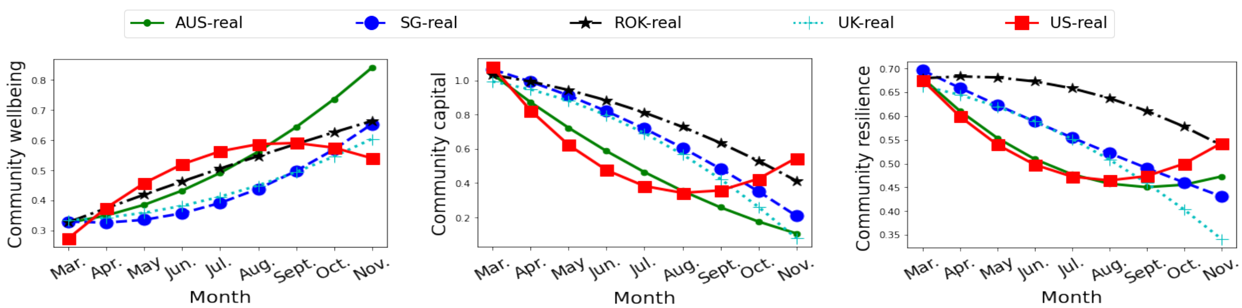
(f) Social wellbeing from real Tweets.

Figure 3.5: Measuring community wellbeing in terms of mental, physical, and social wellbeing using real and fake Tweets for the five countries during the period of Mar.-Nov. 2020.

(2) Overall, both fake and real Tweets show increasing physical wellbeing (PW). However, in fake Tweets, PW surged during the summer and showed downturns. For the US, it is noticeable that the trends shown in fake and real Tweets are almost completely opposite; and (3) Similar to PW, real Tweets show steadily increasing social wellbeing (SW) while fake Tweets had the peak during the summer and showed downturns after then. Some noticeable trends are observed in SG and the US, where the trends of SW are very opposite in fake and real Tweets. In addition, it is quite impressive that AUS shows distinctively steady growth in SW in real Tweets.



(a) Community wellbeing from fake Tweets. (b) Community capital from fake Tweets. (c) Community resilience from fake Tweets.



(d) Community wellbeing from real Tweets. (e) Community capital from real Tweets. (f) Community resilience from real Tweets.

Figure 3.6: Community wellbeing, community capital, and community resilience measured based on COVID-19 related real and fake Tweets for the five countries during Mar.-Nov. 2020.

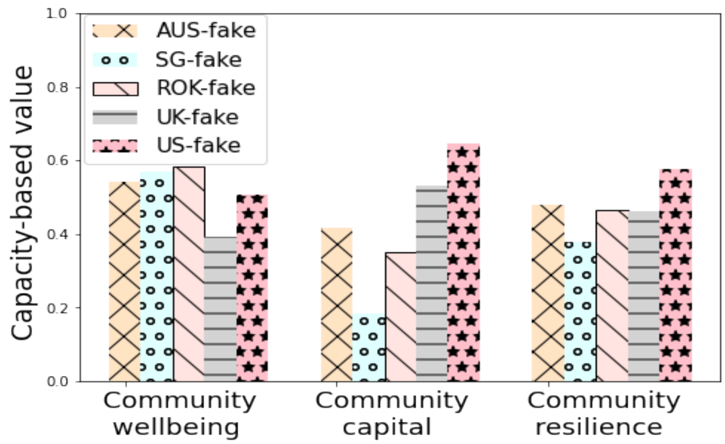
3.3.4 Community Wellbeing, Capital, and Resilience

Finally, we demonstrate the measured community wellbeing, capital, and resilience (i.e., CW, CC, and CR, respectively) based on the metrics described. Fig. 3.6 shows CW, CC, and CR using fake and real Tweets under the five countries.

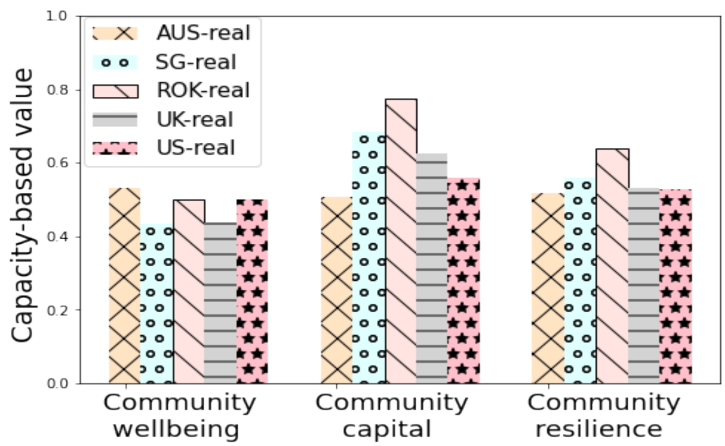
Recall that CR is a function of CW and CC, and we addressed the three wellbeing measures of CW as well as the three aspects of social wellbeing in Figs. 3.4 and 3.5, respectively. Hence, the measures of CR are naturally affected by the measures of CW and CC. We observed the following general trends from Fig. 3.6: (1) In both fake and real Tweets, we observed the increasing trends in CW. In particular, high CW in real Tweets is very noticeable during the Oct.-Nov. timeline. Again, the opposite trends between fake and real Tweets in the US are observed as we observed in Figs. 3.4 and 3.5; (2) For CC, the general trends are decreasing in both fake and real Tweets although fake Tweets show slight resurgence from the Sep. timeline. This would be because of business shutdown policies activated by the governments; and (3) Finally, in CR, although we observed increasing trends in both fake and real Tweets under CW, due to the decreasing trends in CC, the overall CR in fake and real Tweets are still in decreasing trends. But from the Sep. timeline, the fake Tweets show increasing turns for CR.

According to the resilience literature, there are two types of resilience measurements: output-oriented and capacity-based [111]. We have discussed how to measure CR in an output-oriented manner using community functionality in Section **??**. While output-oriented measurements yield accurate information about the trend and dynamic change of functionality, capacity-based measurements yield detailed information about overall functionality.

Fig. 3.7 demonstrates the capacity-based levels of CW, CC, and CR as measured by real and fake Tweets under the five countries. According to our findings, real Tweets result in up to 80% greater CR and CC than fake Tweets. On the other hand, the CW from fake Tweets is 40% more than that of real Tweets. The results in ROK and SG are higher than the other three countries under real Tweets. On the other hand, under fake Tweets, the US is the most resilient country while SG is the least resilient country. The difference in CR between real and fake Tweets demonstrates how social media affects CR where the difference is 0.04, 0.18, 0.17, 0.07, and 0.05, corresponding to the AUS, SG, ROK, and UK, and the US, respectively. As we observe, SG and ROK are highly affected by fake Tweets.



(a) Capacity-based CW, CC, and CR from fake Tweets.



(b) Capacity-based CW, CC, and CR from real Tweets.

Figure 3.7: The summary of the capacity-based value of reliance-related metrics: community wellbeing, capital, and resilience.

3.3.5 Correlation of the CR Between Fake and Real Tweets

To better understand the correlation of resilience measures between fake and real Tweets, we calculate their statistical correlation coefficients based on Pearson's and Spearman's correlation coefficients. These two correlation metrics demonstrate the linear and monotonic relationships between two variables, x, and y [112]. Table 3.5 shows Pearson's and Spearman's correlation coefficients of each resilience measure when fake and real Tweets are used under the five countries. This table illustrates the correlations based on the data obtained

Table 3.5: Pearson and Spearman Correlation Coefficients of CR and Its Associated Attributes Between Fake and Real Tweets Under the Five Countries After Removing Outliers.

CR attributes	Countries	AUS		SG		ROK		UK		US		All	
	Coeff.	Pear.	Spear.	Pear.	Spear.	Pear.	Spear.	Pear.	Spear.	Pear.	Spear.	Pear.	Spear.
Community Wellbeing	Mental	-0.67	-0.77	0.11	-0.17	0.37	0.43	-0.91	-0.88	-0.99	-0.92	-0.61	-0.63
	Physical	0.83	0.63	0.74	0.78	0.71	0.78	0.66	0.63	0.99	0.95	0.83	0.63
	Social	-0.29	-0.17	0.56	0.4	-0.99	-1	-0.97	-0.82	-0.38	-0.58	-0.96	-1
Social Wellbeing	Social	0.96	0.98	0.7	0.88	0.78	0.78	0.1	0.17	-0.95	-0.78	0.75	0.63
	Family	0.41	0.43	-1	-1	0.01	0.17	-0.85	-0.63	-0.98	-0.95	-0.87	-0.95
	Work	-0.94	-1	-0.98	-0.82	0.05	-0.07	-0.97	-1	-0.99	-0.97	-1	-1
Community wellbeing		0.75	0.63	0.44	0.43	0.3	0.43	0.03	0.17	-0.73	-0.93	0.45	0.43
Community capital		0.87	0.98	-0.66	-0.77	0.52	0.43	0.13	0.17	-0.81	-0.78	0.56	0.43
Community resilience		0.72	0.4	0.84	0.78	0.59	0.73	0.79	0.88	0.96	0.82	0.91	0.78

by fitting a function with the maximum likelihood using non-linear least squares regression. In general, the two correlation coefficients are highly similar, indicating high consistency in correlations (i.e., both positive and negative correlations), except for the two cases: 1) SG's 'mental wellbeing' 2) 'Work' as a determinant of social wellbeing in the ROK. Nonetheless, the correlation coefficients for both cases are low, resulting in these two correlations having opposite signs. Except for the SG and US, the correlations between CC measured by fake Tweets and real Tweets are positive under all three countries. We also observed similar correlations under CW in all the countries, except the US, which are positive. The correlations of CR are positive under each country and all five countries (i.e., under All). In other words, as the level of CR related to fake Tweets increases, the level of CR associated with real Tweets increases as well.

Chapter 4

Measuring Community Resilience During the COVID-19 based on Community Wellbeing and Resource Distribution

This chapter measures and analyzes community resilience based on community wellbeing and resource distribution using social media information, including both news articles and Tweets. This chapter is based on our submitted paper in [26].

4.1 Community Resilience Metrics

We measure the community functionality in terms of community wellbeing and resource distribution. Fig. 4.1 represents the community functionality, $CF(t)$, with time t.

We define community resilience based on the concept of system resilience [50] consisting of absorption (i.e., fault tolerance), adaptability, and recoverability. We interpret the time until a community does not function as the time period for absorption, namely TFA (i.e., time from t_0 to t_1). Absorption (ABS) refers to the community's capacity to absorb the shock

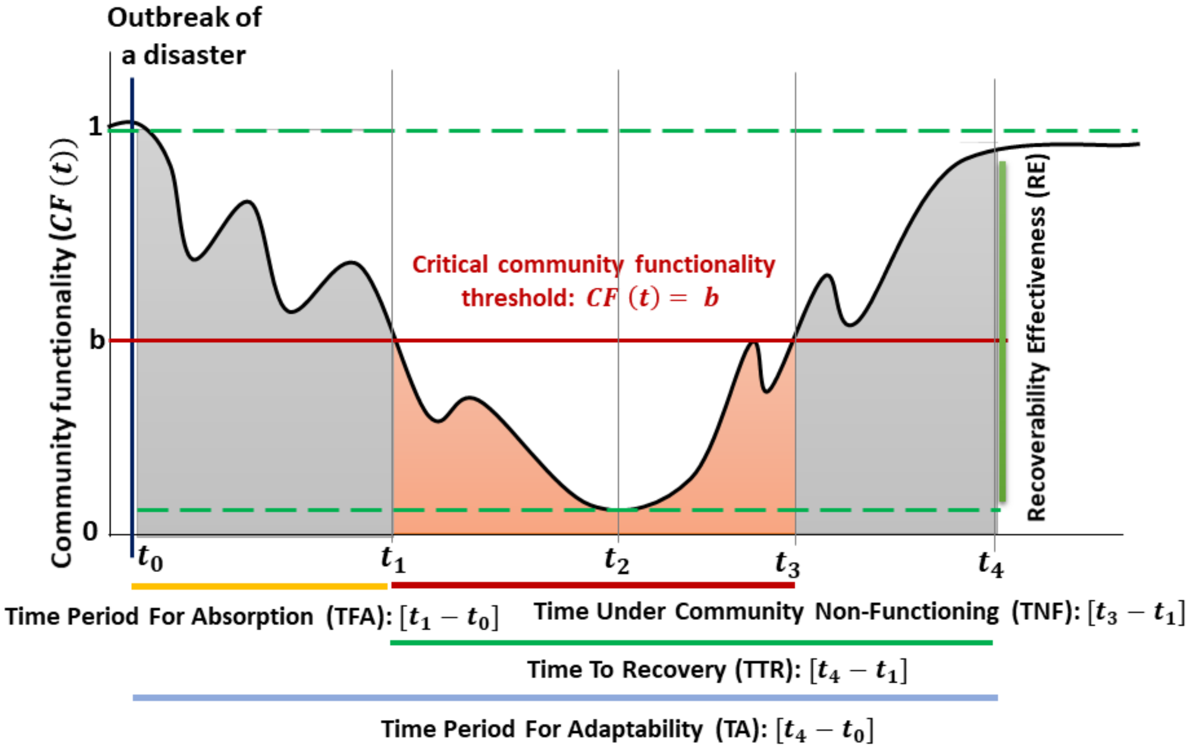


Figure 4.1: The evolution of community functionality ($CF(t)$) from the outbreak of a disaster (e.g., COVID-19) to the full recovery of a community.

and adverse effects caused by COVID-19. High TFA implies that the community tolerates hardships introduced by a disaster so that the community can still function by providing at least critical, minimum services, such as food, employment, schools, or health services. Note that a high level of absorption is desirable. Community Non-Functioning (CNF) is a term that refers to situations in which the community's functionality falls below a critical threshold. We denote the deadlock functionality threshold by b. We call the time from t_1 to t_3 the *time under community non-functioning* (TNF). A shorter TNF is considered more desirable, representing fast failure and fast recovery. By following the conventional concept of system reliability, *the meantime to recovery* (MTTR), we defined the time to recovery (TTR) estimated from the time the community reaches a critical functionality point (t_1) to the time it fully recovers from the disaster and reaches at the initial normal state (t_4). Recovery (REF) refers to the community's capacity to recover from COVID-19.

The recoverability effectiveness (RE) refers to how much the community has recovered from the minimum functionality point, t_2, to the current point at t_4. Note that a high level of recovery is desirable. We consider the whole period from the outbreak of a disaster (e.g., COVID-19) to the time a community is fully recovered, t_4, as the time period for adaptability (TA). Depending on how the community handles the disaster, TA may not include TNF but directly recover from a less functionality state to a full functionality state. It is important to note that a high level of absorption, recovery, and adaptability is desired. In other words, the more area under the curve a community has, the more resilient it is.

We estimate $CF(t)$ based on the levels of community wellbeing ($CW(t)$) and resource distribution ($RD(t)$) at time t. Hence, the community resilience (CR) is measured by:

$$CR_{[a,b]} = \int_{t=a}^{b} CF(t)\, dt = \int_{t=a}^{b} \frac{CW(t) + RD(t)}{2}\, dt, \tag{4.1}$$

where $[a, b]$ denotes the time period used to calculate the CR. CW and RD are treated equally in this work. On the other hand, CW and RD can be weighted differently depending on the relative importance of CR in a given domain. For fair consideration of each component, we use a normalized value of CW and RD as a real number ranged in $[0, 1]$ using *min-max scaling* [89].

To determine the average community functionality across the COVID-19's time periods, we measure ABS, CNF, and REF as follows:

- *Absorption (ABS)* refers to the average community functionality during the time period for absorption. It is estimated by:

$$ABS = \frac{\int_{t_0}^{t_1} CF(t)}{t_1 - t_0}. \tag{4.2}$$

- *Community Non-Functioning (CNF)* indicates the average community functionality over the time under critical area of community functionality. It is measured by:

$$CNF = \frac{\int_{t_1}^{t_3} CF(t)}{t_3 - t_1}. \tag{4.3}$$

  We assume that a community is entirely dysfunctional when its CR is below threshold b.

- *Recovery (REF)* means the average community functionality during the time to recovery and is obtained by:

$$REF = \frac{\int_{t_1}^{t_4} CF(t)}{t_4 - t_1}. \tag{4.4}$$

We constructed a more straightforward framework for CR in Chapter 3, where we assessed the CR measures of five nations using Twitter datasets. We employed machine learning classifiers in this framework to determine if the news is true or false. While we focus exclusively on the United States in the second framework of evaluating CR, we build thorough CR indicators that incorporate both Tweets and fake news as external factors. Community wellbeing (CW) and resource distribution (RD) are considered as key indicators of CR. Here, community capital (CC) is the primary component of RD in this concept. Similar to the previous framework, we used machine learning classifiers in this framework to determine if the news is true or false. Additionally, we evaluated true, mixed, and fake news as determined by fact-checking organizations, such as Snopes, FactCheck, PolitiFact, and Poynter.

Now we discuss how to estimate CW and RD in detail as below.

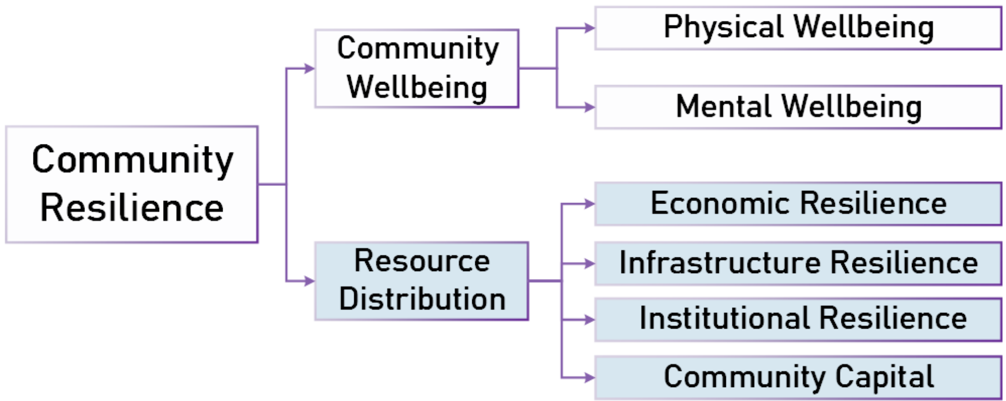


Figure 4.2: The proposed community resilience metrics consisting of community wellbeing and resource distribution.

4.1.1 Measuring Community Wellbeing

A lack of community wellbeing (CW) under disasters can increase people's vulnerability to early deaths or injuries or triggers irrational behavior, such as panic buying [113]. The CW is given by:

$$CW = \frac{MW(t) + PW(t)}{2}, \tag{4.5}$$

where $MW(t)$ and $PW(t)$ represent mental and physical wellbeing at time t, respectively, and each component is considered with equal weight. Each dimension of wellbeing can be assigned a different weight depending on the domain requirement. The mental and physical wellbeing is estimated using NLP tools as follows:

- *Mental wellbeing* is measured by the extent of people's moods, such as anxiety, depression, and anger, which have long been recognized as typical symptoms of mental illness [8, 92, 93]. We use *anxiety, sadness*, and *anger*, which are the features obtainable using linguistic inquiry, word count (LIWC) categories, to obtain the extent of community mental wellbeing.

- *Physical wellbeing* is measured by the following features:

  – *First-person singular pronouns*: According to language psychology [94], the frequent use of first-person singular pronouns may indicate physical pain and an increased focus on one's self [94]. We measure this language pattern using the LIWC category of 'first-person singular' to estimate physical wellbeing.

  – *Words representing physical activities and health*: The extent to which one engages in physical activities and maintains good health is determined by the increased use of motion (e.g., 'arrive,' 'go,' 'car'), leisure (e.g., 'cook,' 'chat,' 'movie'), work-related (e.g., 'job,' 'majors,' 'xerox'), health-related (e.g., 'fitness,' 'healthiness,' or 'wellness'), and positive body-related terms (e.g., 'hands,' 'cheek,' and 'spit') [95, 96, 97, 98]. We measure these language patterns using the LIWC categories of 'motion,' 'work,' 'leisure,' 'health,' and 'body.'

4.1.2 Measuring Resource Distribution

Resource distribution (RD) also measures part of CR [5, 7, 28, 64] where the high functionality in RD refers to the high ability that a community can provide services to its inhabitants related to economic, infrastructure, institutional, and community capital resources. We assume that sufficient and well-distributed resources can contribute to the community that can better resist, recover, and/or overcomes a disaster. We measure RD in terms of how well each service is provided. RD is measured by:

$$RD = \frac{EF(t) + IF(t) + ITF(t) + CCF(t)}{4}, \tag{4.6}$$

where $EF(t)$, $IF(t)$, $ITF(t)$, and $CCF(t)$ refer to the level of states related to economic, infrastructural, institutional, and community capital functionality, respectively, with an equal weight considered. Again, depending on the domain requirement, its weight can be differently considered. Each component of RD, including $EF(t)$, $IF(t)$, $ITF(t)$, and $CCF(t)$, is measured by LIWC categories as follows:

- *Economic functionality* (EF) is the economic capacity of a given community before and after a disaster. The examples include housing capital, employment, income, signal sector employment dependence, or business sizes. Economic functionality is captured by extracting the number of words related to money or work, such as the increased use of work-related (e.g., 'job,' 'majors,' 'xerox'), money-related (e.g., 'Audit,' 'cash,' or 'owe') terms in the LIWC categories.

- *Infrastructure functionality* (IF) is a community's infrastructural capacity. The Department of Homeland Security [114] categorizes 16 critical infrastructures, e.g., energy, transportation, and emergency services [34, 39, 115, 116, 117]. This functionality is measured by extracting the amount of works related to health (e.g., emergency services) and motion (i.e., transportation infrastructure). This capacity is measured based on the increased use of motion (e.g., 'arrive,' 'go,' 'car'), and health-related (e.g., 'fitness,' 'healthiness,' or 'wellness') terms in the LIWC categories.

- *Institutional functionality* (ITF) refers to a community's capacity in its religious, educational, or social organizations. Institutional resources can include mitigation (% of the population covered by Citizen Corps programs), flood coverage, municipal service, political fragmentation, social connectivity (% of 1-person households), previous disaster experience (i.e., disaster frequency), and municipal service (e.g., percentages of municipal expenditures for fire, police, or emergency management services). This

ITF is measured by extracting the number of words related to 'achieve,' 'reward,' and 'assent.' The ITF is measured by the increased use of achieve-related (e.g., 'earn,' 'hero,' 'win'), reward-related (e.g., 'prize,' 'benefit,' 'profit'), assent-related languages (e.g., 'agree,' 'OK,' 'yes') in the LIWC categories [106].

- *Community capital* indicates a community's ability to provide social activity services to its inhabitants and build trust among them. We assess community capital in terms of the language patterns representing community cooperation using the LIWC categories as follows:

  - *Communication Efficiency*: The increased use of complex words and words with more than six letters has been identified as being inefficient for communication and cooperation [104]. To measure this, we calculate the opposite degree of 'Words> 6 letters.'
  - *Group-Oriented Communications*: The frequent use of first-person pronouns, such as 'we,' 'us,' 'our,' indicates group interaction [105]. In psychological linguistics, it is known that assent-related languages (e.g., 'agree, 'OK,' 'yes') point to group consensus and cooperation [106]. Hence, we measure the frequency of words using the 'first-person plural' pronounces and 'assent' in the LIWC categories.
  - *Social Process-Related Communications*: We measure increased social engagement and cooperation [35, 107, 108] based on the frequency of social process languages obtained by 'friend' and 'family.'

The presence of more words within a category indicates a higher value. For a fair comparison, we normalize the value of each attribute in CR by dividing the accumulated degree by the number of words, representing the extent of each attribute ranged in $[0, 1]$ as a real number.

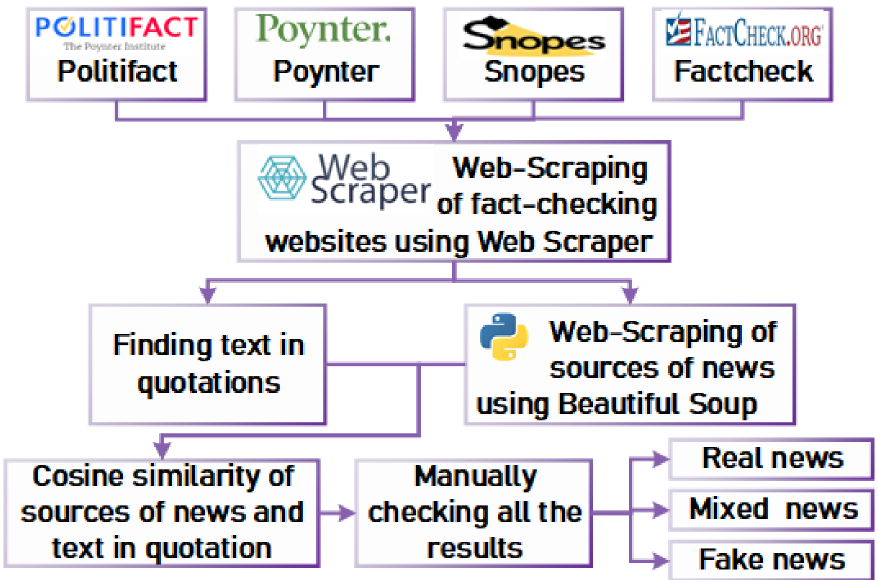


Figure 4.3: Collecting news based on web-scraping and manual cleaning.

4.2 Procedures of Measuring CR via Social Media Information

4.2.1 Collecting News Using Web-Scraping

We describe the process of finalizing information associated with news in Fig. 4.3.

The information includes the text of news articles, issues, subjects, misconceptions, and the title of news articles for all the articles published over time. We use a two-stage web-scraping method to collect these contents. The web crawling process begins with the Google Chrome Extension 'Web Scraper – Free Web-Scraping' [118]. This tool allows interaction with the website from which we scrape data to identify the HTML tags required to extract data from fact-checking websites. We can export the results as a CSV file containing external links to the original articles. Then, we use the Python library Beautiful Soup [119] to analyze external links and scrap the original articles and additional tags that were difficult to web-scrape with

Table 4.1: News types based on the classifications of three fact-checking organizations

Type of news	Snopes	Politifact	Poynter	Factcheck
Real	true, mostly true	true, mostly true	-	-
Fake	mostly false, false	mostly false, false, pants on fire	fake	fake
Mixed	mixture	half true	-	-
Number	2,413	927	1,308	304

the first tool. Additionally, we extract the quotation's text from news scraped from fact-checking organizations. Then, we compare the *cosine similarity* [120] of this quoted text to the news obtained via external links to choose the most appropriate news text automatically and double-check them manually. Note that we filter the so-called 'most appropriate news' by capturing the original news text. The original news text is filtered out by excluding text quoted from other sources. We leverage the automatic web-scraping techniques to capture only the original news text solely written by the author of the given news article.

4.2.2 Classification of News Articles

We extract 4,952 real, mixed, and fake news articles talking about COVID-19 based on the results of four fact-checking organizations, including Snopes [121], Politifact [122], Poynter [123], and Factcheck [124]. We gather 2413, 927, 1308, and 304 news articles talking about COVID-19 for Jan. 2020 - Jun. 2021 from these four organizations, respectively. It is not uncommon for fake news to be examined by several facts checking organizations. According to our datasets, no disagreement is found between these fact-checking outcomes across organizations. The categories of Snopes of interest include true, mostly true, mixture, mostly false, false news. Similarly, Politifact uses tag news with true, mostly true, half true, mostly false, false, and pants on fire news. We categorize news articles into real, mixed, or fake, as described in Tables 4.1. Using these classifications, we collect all news articles from the archived news regarding COVID-19 from these organizations for Jan. 2020 - Jun. 2021.

4.2.3 Processing of News Articles for Analysis

We extract 3,437 news articles tagged with COVID-19 and coronavirus. After processing the initial cleaning, such as checking news with a correct tag, we came up with 3,235 news, consisting of 360 real news, 207 mixed news, and 2,668 fake news. After eliminating repetitive or irrelevant news, we select 207 news at random out of each pool of different types of news for fair consideration. Table 4.2- 4.3 provides the distribution of published news and Tweets considered across months. As in Table 4.2- 4.3, we observe a significant amount of news articles published in Mar./Apr. 2020 and prominently, there is a higher amount of fake news and Tweets compared to those of real counterparts.

Table 4.2: The numbers of various types of news and Tweets per month of the year 2020 considered in this study.

	Month	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
News	Real	0	3	35	47	27	18	28	16	12	15	8	32
	Mixed	0	2	29	35	24	6	10	5	7	8	13	11
	Fake	49	120	485	468	267	108	131	87	77	116	60	122
	All	49	125	549	550	318	132	169	108	96	139	81	165
Tweets	Real	124	81	316	208	138	91	46	40	29	35	20	196
	Fake	1993	1378	8463	5644	3391	1989	1364	904	720	894	559	3304
	All	2117	1459	8779	5852	3529	2080	1410	944	749	929	579	3500

Table 4.3: The numbers of various types of news and Tweets per month of the year 2021 considered in this study.

	Month	Jan.	Feb.	Mar.	Apr.	May	Jun.	All
News	Real	27	13	23	25	21	10	360
	Mixed	16	13	10	7	9	2	207
	Fake	61	86	129	115	126	61	2668
	All	104	112	162	147	156	73	3235
Tweets	Real	114	88	87	93	83	76	1865
	Fake	2716	2018	1762	1852	1854	1595	42400
	All	2830	2106	1849	1945	1937	1671	44265

The news sources are mainly newspaper interviews, TV interviews, viral images, Journals, Press releases, digital ads, campaign ads, meeting in white houses, Story, TV segments, social media, or press conferences. The news is in the format of photos, infographics, videos, text, or interviews. As photos, infographics, videos, or interviews are not in the format of the text, there is a challenge to analyze them. The fact-checking organizations put text and explanations related to each of them. Hence, we use the text generated by the fact-checking organizations to analyze them. We also use the converted format of the photo, infographic, or video for our analysis. We use the release date of the news to determine when a news article is published. The fact-checking organizations (i.e., Snopes, Politifact, Poynter, and Factcheck) categorize news into various classes based on Table 4.1.

4.2.4 Collecting COVID-19-Related Tweets

We investigate 42,877,312 Tweet IDs for Jan. 2020 – Jun. 2021. After removing non-English Tweets, we end up with 44,265 Tweets. Then, we order these Tweets chronologically, whose distribution is shown in Table 4.2. Similar to the news distribution, we observe a significant amount of Tweets generated during Mar./Apr. 2020.

4.2.5 Classifying All Tweets as Real or Fake Based on Three machine learning (ML) Classifiers

We first classify Tweets as real or fake. We first train eight existing ML classifiers on the datasets described in [109], which contain 23,481 fake Tweets and 21,417 real news articles. We then select the top three ML classifiers, i.e., Passive-Aggressive, Decision Tree, and AdaBoost, based on their prediction performance, as shown in Table 4.4. We predict the truthfulness of each Tweet using these three ML algorithms and determine the final prediction for each Tweet based on the majority rule of the three ML classifiers (i.e., at least 2 ML classifiers should give the same prediction result).

Table 4.4: Prediction Performance of Various Machine Learning Classifiers

ML Classifier	Accuracy	Precision	Recall	F-score
Passive Aggressive	0.995	0.995	0.995	0.995
Logistic Regression	0.984	0.984	0.984	0.984
Bagging Classifier	0.618	0.779	0.598	0.532
K-Neighbors	0.671	0.782	0.655	0.622
Decision Tree	0.994	0.994	0.994	0.994
Random Forest	0.519	0.623	0.5	0.346
AdaBoost	0.995	0.995	0.995	0.995
Multi Layer Perceptron	0.966	0.967	0.966	0.966

4.2.6 Identifying Physical-Psycho-Social States and Behavioral Patterns using LIWC

We use the LIWC as our text-mining tool for the analyses of COVID-19 related news and Tweets because it contains a wealth of physical-psychosocial characteristics and behavioral patterns. Due to the unstructured language, short message lengths, dynamic nature, and variability of Twitter data streams, developing and maintaining supervised learning systems is technically challenging and time-consuming [125]. Prior to analyzing them with the LIWC, all Tweets are sorted by month and cleaned using various NLP tools (i.e., nltk, string, stopwords, RegexpTokenizer, and regexp) for each type of news (i.e., real, mixed, or fake) and Tweet (i.e., real or fake). We begin text cleaning by removing HTML, punctuation, stop words, and stammering words. Following that, we extract all LIWC features relevant to CR assessment.

4.3 Numerical Results & Analyses

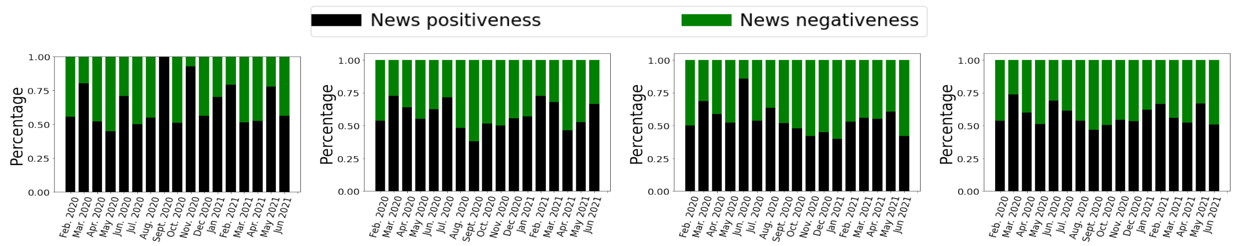
4.3.1 News Analyses: Word Cloud and Sentiments

Fig. 4.4 illustrates the word cloud associated with real, mixed, fake, and all news. Fig. 4.5 plots the positive and negative sentiments associated with various types of news over time. The subject frequency of various types of news is shown in Table 4.5. Politics is the most frequently covered subject. Also, medical and health, entertainment, and business are all popular topics that can affect community resilience. In May and Sep. 2020, real news has the least positive and negative sentiment. In Sep. 2020 and Mar. 2020, mixed news has the least positive and negative content. In Jan. 2021 and Jun. 2020, fake news has the least positive and negative sentiment. In Sep. and Mar. 2020, all news is at its least positive and least negative, respectively. The subject of each news item is determined by fact-checking organizations, such as Snopes and Politifact.

(a) Real news (b) Mixed news (c) Fake news (d) All news

Figure 4.4: Word cloud for real, mixed, fake, and all news for Jan. 2020 – Jun. 2021.

Additional results from the sentiment analyses using news titles captured by different fact-checking organizations, including Snopes, Politifact, and Factcheck, are shown in the appendix C.



(a) Real news (b) Mixed news (c) Fake news (d) All news

Figure 4.5: The positiveness and negativeness of news about the COVID-19 for Jan. 2020 – Jun. 2021.

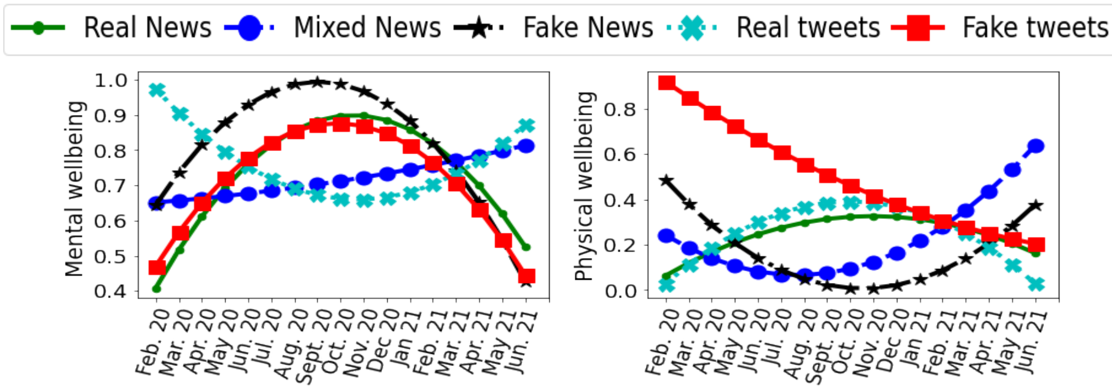
Table 4.5: Subject frequency of Various News Types Collected for Jan. 2020 – Jun. 2021.

Source	Subject (an amount of news)
Real news	politics (87), medical (29), fauxtography (17), entertainment (13), business (12), viral (5), phenomena (5), crime (5), history (5), health (5)
Mixed news	coronavirus (67), politics (48), health (32), facebook (29), public (19), medical (17), fact (16), checks (16), posts (10), budget (8)
Fake news	politics (97), medical (39), fauxtography (13), entertainment (9), junk (9), news (9), viral (7), phenomena (7), technology (6), business (5)
All news	politics (229), medical (84), coronavirus (67), health (38), fauxtography (31), facebook (29), entertainment (23), business (22), public (17), fact (16)

4.3.2 Mental and Physical Wellbeing Assessment

From Feb. 2020 to Jun. 2021, Fig. 4.6 depicts the normalized degree of mental wellbeing (MW) and physical wellbeing (PW) as measured by real, mixed, and fake news as well as real and fake Tweets.

Fig. 4.6(a) shows that fake news and fake Tweets demonstrate similar MW patterns. The peak of MW in fake Tweets and real/fake news occurs in Sep. 2020. On the other hand, the peaks of MW in real Tweets and mixed news occur in Feb. 2020 and Jun. 2021, respectively. We also observe that MW reaches its lowest point by the end of 2020 under real Tweets. This result aligns well with the trends reported by the US Census Bureau [126] that since the COVID-19 outbreak in Feb. 2020, people's MW has deteriorated by the end of 2020. Fig. 4.6(b) shows that PW under real news and Tweets reveal similar patterns. Also, PW



(a) Mental wellbeing

(b) Physical wellbeing

Figure 4.6: Community wellbeing based on mental wellbeing and physical wellbeing measured by different types of news (i.e., real, mixed, and fake) and Tweets (i.e., real and fake).

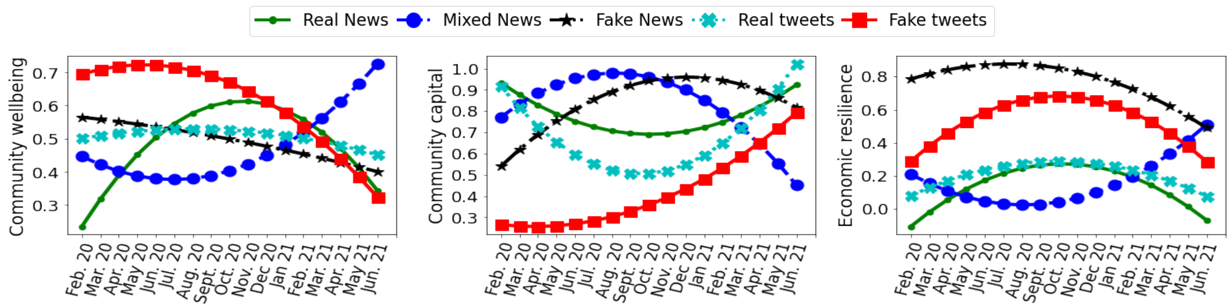
under fake and mixed news exhibit similar patterns. PW associated with mixed/fake news and fake Tweets reduces between Feb. and Sep. 2020 while that associated with real news and real Tweets grows month by month. We observe the highest PW in Oct. 2020 under real Tweets and real news. On the other hand, PW reached its peak in Feb. 2020 under fake Tweets and fake news.

4.3.3 Output-Oriented Resilience Assessment

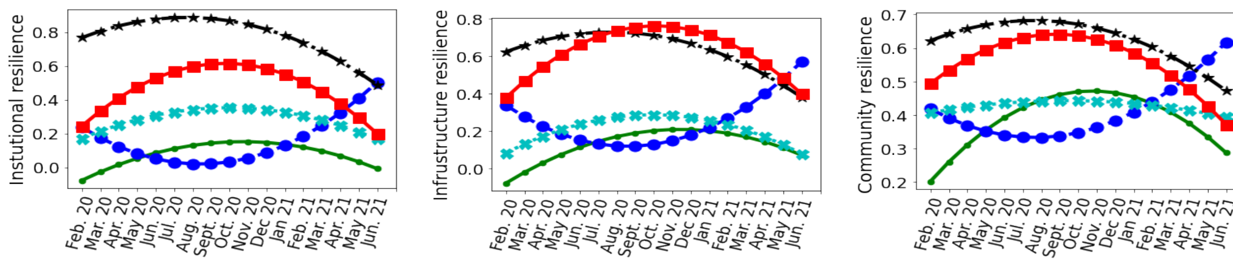
The output-oriented analysis measurements provide accurate information about the trend and dynamic change of functionality in a given community [111]. We measure CR over time (i.e., Feb. 2020 to Jun. 2021) for this out-oriented resilience assessment. Fig. 4.7 illustrates the degree of community wellbeing, community capital, economic resilience, institutional resilience, infrastructure resilience, and community resilience measured by the news (i.e., real, mixed, and fake) and Tweets (i.e., real and fake) collected for Feb. 2020 – Jun. 2021.

Additional output-based resilience assessment results using news titles and Tweets collected for Feb. 2020–Jun. 2021 can be found in appendix C.

From this figure, we observe that real Tweets and real news typically follow similar trends.



(a) Community wellbeing. (b) Community capital. (c) Economic resilience.



(d) Institutional resilience. (e) Infrastructure resilience. (f) Community resilience .

Figure 4.7: Community wellbeing, community capital, economic resilience, institutional resilience, infrastructure resilience, and community resilience measured based on different types of news and Tweets for Feb. 2020–Jun. 2021.

Similarly, fake Tweets and fake news also exhibit similar trends. For real news and Tweets, wellbeing, institutional, infrastructure, economic, and community functionalities are at their peak in Sep. 2020, while community capital is at the lowest level. Community capital shows its trend in the opposite direction of other functionalities. This is because when a community is threatened due to the impact introduced by a disaster, people are more likely to cooperate for survival. On the other hand, community capital shows an opposite trend under mixed/fake news and fake Tweets. Although community resilience begins to improve at the end of 2020, it also begins to deteriorate in 2021. In 2021, people's wellbeing has been worsened. This is probably because people become tired of long-term restrictions in their daily lives, such as social distancing, online schooling/working, especially with the emergence of COVID-19 variants. These factors may drive people to become more pessimistic about the full recovery from the pandemic.

4.3.4 Capacity-based Resilience Assessment

Capacity-based measurements are time-averaged community resilience measurements of a given community, indicating the degree of functionality of the community [111]. Fig. 4.8 illustrates the capacity-based values of all resilience-related metrics, including community wellbeing, community capital, economic resilience, institutional resilience, infrastructure resilience, and finally, community resilience (CR), measured using real, mixed, and fake news as well as real and fake Tweets.

We see from Fig. 4.8 that Fake Tweets are in a better state of community wellbeing. The reason is that people believe community wellbeing is adequate and likely underestimate the detrimental effect of COVID-19. We often hear people saying, "This disease is not for me, and I will never get infected," indicating that people believe they are more isolated than what the news indicates. Additionally, their communication via fake Tweets demonstrates a significant level of isolation, whereas real Tweets show a higher level of community capital. Fig. 4.8 shows that while fake news presents a high degree of economic resilience, real news shows a low degree of economic resilience under COVID-19. The reason is that rumors or fake news trigger panic buying, thus eroding economic resilience. While fake Tweets and fake news demonstrate a high degree of institutional resilience, real Tweets, and real/mixed news demonstrate a low degree of institutional resilience. The reason is that people believe community functionality is still efficient during COVID-19, but in reality, it is not the case. Infrastructure resilience is similar to institutional resilience in that fake Tweets and fake news demonstrate a higher level of resilience than real Tweets and real/mixed news. The reason is that based on false information, the community believes that critical infrastructures such as emergency services, hospitals, and transportation will operate normally during COVID-19. Finally, fake news and fake Tweets show higher community resilience than real news and real Tweets. Fake news has the potential to mislead people into taking inappropriate actions

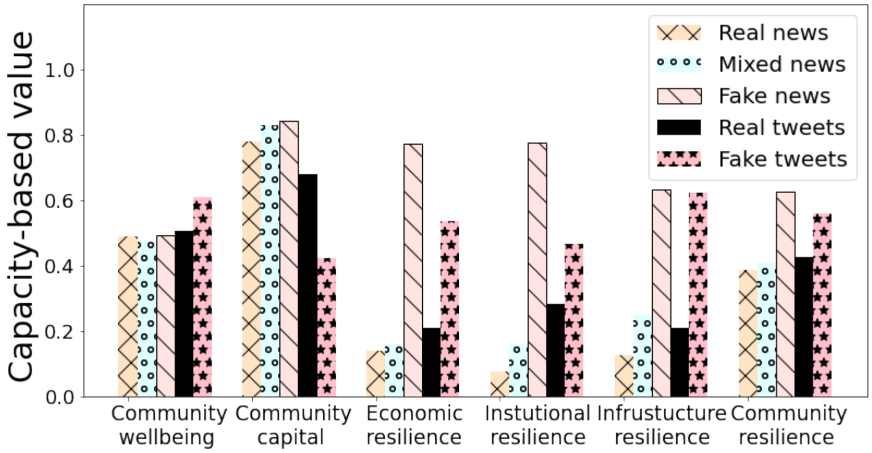


Figure 4.8: Capacity-based analysis of community wellbeing, community capital, economic resilience, institutional resilience, infrastructure resilience, and community resilience.

in response to COVID-19 by forming unrealistic optimism about the future. For instance, some fake news suggests that smoking, self-medicating with antibiotics, and wearing multiple surgical masks are helpful to combat COVID-19. This information is not only impractical but also potentially jeopardizing community resilience.

Table 4.6 shows the measurement values of community functionality metrics, including Absorption (ABS), Community Non-Functioning (CNF), Recovery (REC), Time for Absorption (TFA), Time under Community Non-Functioning (TNF), and Time To Recovery (TTR) (see Fig. 4.1) for news and Tweets, with the critical community functionality threshold, b, varying in the range of 0.2 to 0.5 in increment of 0.1.

Fake Tweets and news induce the highest level of absorption for all critical community functionality threshold values. Additionally, fake news typically exhibits the greatest degree of recovery. Fake news fosters distrust among the public, despite the fact that trust is a critical component of transparent risk communication, collaboration, and the cooperation of individuals to overcome catastrophic events. The results suggest that negative outputs of fake news create problems not only in handling COVID-19 but also in recovering from it. Real news induces a 17-month recovery for all critical community functionality threshold values,

Table 4.6: Absorption (ABS), Community Non-Functioning (CNF), Recovery (REC), Time for Absorption (TFA), Time under Community Non-Functioning (TNF), and Time To Recovery (TTR) for News and Tweets with the Critical Community Functionality Threshold, b, varying over the range of 0.2-0.5.

CR Indexes	$b = 0.2$					$b = 0.3$				
	News			Tweets		News			Tweets	
	Real	Mixed	Fake	Real	Fake	Real	Mixed	Fake	Real	Fake
ABS	0.20	0.36	0.62	0.43	0.56	0	0.36	0.62	0.43	0.56
CNF	0	0	0	0	0	0.25	0	0	0	0
REC	0.39	0.43	0.47	0.39	0.37	0.39	0.43	0.47	0.39	0.37
TFA	1	7	17	17	17	0	7	17	17	17
TNF	0	0	0	0	0	3	0	0	0	0
TTR	17	11	1	1	1	17	11	1	1	1

CR Indexes	$b = 0.4$					$b = 0.5$				
	News			Tweets		News			Tweets	
	Real	Mixed	Fake	Real	Fake	Real	Mixed	Fake	Real	Fake
ABS	0	0.42	0.62	0.43	0.57	0	0	0.63	0	0
CNF	0.31	0.35	0	0.39	0.37	0.39	0.38	0.47	0.43	0.44
REC	0.39	0.41	0.47	0.39	0.37	0.39	0.41	0.47	0.43	0.56
TFA	0	1	17	16	16	0	0	16	0	0
TNF	8	10	0	1	1	17	14	1	17	4
TTR	17	16	1	1	1	17	17	1	17	17

Note that TFA, TNF, and TTR refer to the month-based average values.

while the absorption level is 0-1 month. This means that community resilience is steadily increasing from Feb. 2020 to Jun. 2021. In other words, with real news, the community can recover very quickly following the initial degradation of functionality. Additionally, the number of months during which the community is non-functioning ranges in 0-17 months, depending on the critical threshold level. For example, TNF is equal to 17 months when b=0.5. This means that the community functionality from the perspective of real news is less than 0.5 for all 17 months. Understandably, as the critical threshold level increases, the time duration associated with community dysfunction and recovery increases, while that associated with absorption decreases. On the other hand, fake news has a higher level of absorption than mixed news. Both fake news and mixed news show a higher level of absorption than of real news. This implies that the level of community functionality is initially high and gradually declines, whereas real news demonstrates a rapid decline in community functionality at the start. For Tweets, both real and fake Tweets exhibit a high absorption level when b=0.2-0.4. This indicates that individuals believe the community is highly functional. Additionally, fake Tweets exhibit a greater level of absorption than real Tweets. Therefore, we can conclude that fake Tweets grossly underestimate the negative impact of COVID-19 on the community.

We summarize the findings obtained from the discussion above as follows:

-Based on fake news, the public would believe the community is resilient, which is not the case. Additionally, the results indicate that fake news shares the same viewpoint. They underestimate COVID-19's adverse effect and demonstrate a high level of resilience in comparison to real news. This perspective prolongs the time required for complete recovery. Additionally, based on this finding, we observe that fake news is not always pessimistic or negative.

-Mixed news is slightly more optimistic than real news in terms of resilience. The most likely reason is that mixed news contains fake news.

- When compared to propagated fake Tweets, propagated fake news is more unrealistic. They demonstrate a greater capacity for community resilience. This is understandable given that the source of fake news frequently intends to cause harm, whereas those who spread fake news may have done so unintentionally.

-Propagated real news is slightly more negative than real Tweets and demonstrates a lower level of community resilience. This is because the source of the news effect typically decreases in either direction during the propagation process.

4.3.5 Statistical Analyses of News and Tweets

Table 4.7 shows the findings from our statistical analyses on the correlation between news and Tweets.

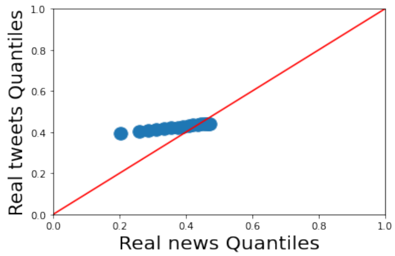
The statistical analyses include Pearson correlation (PC), Kendall tau correlation (KC), parametric statistical hypothesis tests (PT; Student's t-test), and non-parametric statistical hypothesis tests (NT; Mann-Whitney U Test). According to Table 4.7, both fake Tweets and news have a positive correlation with all types of resilience. Pearson and Kendall tau correlations (PC and KC) indicate that the correlations between fake news and Tweets in a measure of community resilience are 0.94 and 0.81, respectively. In addition, we observe that correlations between real news and Tweets are always positive in all measures of CR attributes. Pearson and Kendall tau correlations (PC and KC) demonstrate that the correlations between real news and Tweets in a measure of community resilience are 0.82 and 0.65, respectively. We also found that mixed news negatively correlates with real and fake Tweets across all types of CR attributes. Further, fake news and Tweets have a negative correlation with real news and Tweets in community capital. Parametric and non-parametric statisti-

Table 4.7: The Statistical Analysis of Various Functionalities for Three News Compared To Two Types of Tweets: Pearson Correlation (PC), Kendall Tau Correlation (KC), Parametric Statistical Hypothesis Tests (PT), and Non-Parametric Statistical Hypothesis Tests (NT)

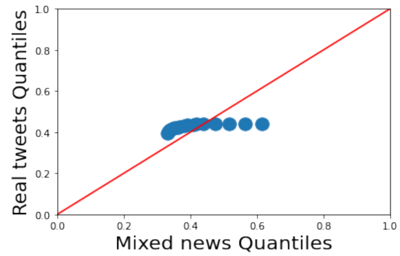
Source			**News**								
Feature			Wellbeing			Community capital			Economic resilience		
Type			Real	Mixed	Fake	Real	Mixed	Fake	Real	Mixed	Fake
Tweets	**PC**	Real	0.51	-0.98	0.74	0.97	-0.88	-0.56	0.99	-0.76	0.63
		Fake	0.14	-0.98	0.94	0.30	-0.86	0.41	0.99	-0.76	0.62
	KC	Real	0.44	-0.75	0.38	0.88	-0.68	-0.47	0.88	-0.68	0.50
		Fake	0.00	-0.81	0.82	0.00	-0.44	0.41	0.88	-0.68	0.50
	PT	Real	✔	✔	✔	✘	✘	✘	✘	✔	✘
		Fake	✘	✘	✘	✘	✘	✘	✘	✘	✘
	NT	Real	✔	✘	✔	✘	✘	✘	✘	✘	✘
		Fake	✘	✘	✘	✘	✘	✘	✘	✘	✘

Source			**News**								
Feature			Institutional resilience			Infrastructure resilience			Community resilience		
Type			Real	Mixed	Fake	Real	Mixed	Fake	Real	Mixed	Fake
Tweets	**PC**	Real	0.94	-0.82	0.70	0.82	-0.85	0.70	0.82	-0.85	0.84
		Fake	0.91	-0.87	0.75	0.86	-0.81	0.65	0.67	-0.95	0.94
	KC	Real	0.76	-0.68	0.59	0.66	-0.78	0.59	0.65	-0.71	0.71
		Fake	0.76	-0.68	0.59	0.78	-0.66	0.47	0.54	-0.81	0.81
	PT	Real	✘	✘	✘	✘	✔	✘	✘	✔	✘
		Fake	✘	✘	✘	✘	✘	✔	✘	✘	✘
	NT	Real	✘	✘	✘	✘	✔	✘	✔	✘	✘
		Fake	✘	✘	✘	✘	✘	✔	✘	✘	✘

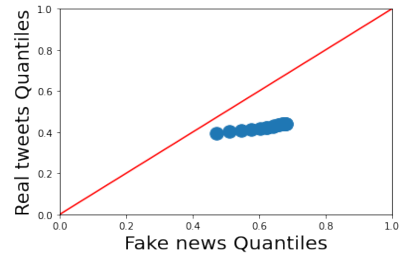
Note that ✔ and ✘ mean following or not following the same distribution, respectively.



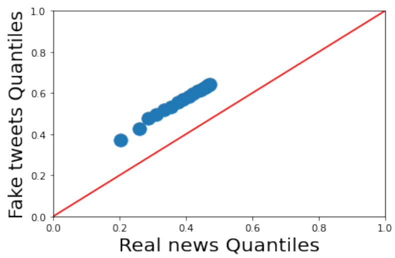
(a) Real Tweets vs. real news



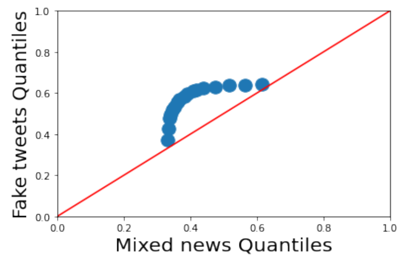
(b) Real Tweets vs. mixed news



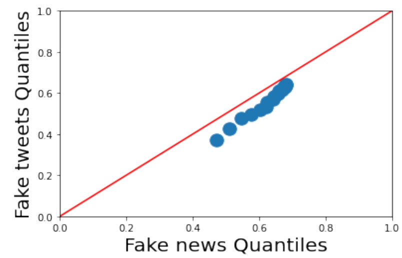
(c) Real Tweets vs. fake news



(d) Fake Tweets vs. real news



(e) Fake Tweets vs. mixed news



(f) Fake Tweets vs. fake news

Figure 4.9: The Quantile-Quantile (Q-Q)-plot of news and Tweets used to measure community resilience where x-axis refers to the quantiles of real, mixed, or fake news and y-axis indicates the quantiles of real, fake, or all Tweets.

cal hypothesis tests (PT and NT) demonstrate the distribution's similarity across multiple scenarios. Fig. 4.9 illustrates the Quantile-Quantile (Q-Q)-plot for community resilience in relation to various news types (i.e., real, mixed, or fake) and Tweet types (i.e., real or fake). We observe that fake news and Tweets exhibit a higher degree of similarity in their distributions than other types of news and Tweets. This implies that both fake and true news and Tweets can properly reflect the actual states of community resilience (CR) regardless of their truthfulness. This implies that analyzing social media information and predicting CR can provide a useful indicator to measure how our community is functioning against a disaster such as COVID-19.

Additional QQ-plots of news and Tweets can be found in the appendix C.

Chapter 5

Conclusions

In this work, we provided valuable insights into assessing community resilience using social media information. To do so, we proposed two frameworks to measure community resilience during COVID-19. We constructed a more straightforward framework for community resilience based on community wellbeing and community capital in Chapter 3, where we assessed the community resilience of the five nations using Twitter datasets. We employed machine learning classifiers in this framework to determine if the news is true or false. While we focus exclusively on the United States in the second framework of evaluating community resilience, we developed thorough community resilience indicators considering both Tweets and fake news as external factors. Community wellbeing and resource distribution are indicators of community resilience. Here, community capital is the primary component of resource distribution in this concept. Similar to the previous framework, we used machine learning classifiers in this framework to determine if the news is true or false. Additionally, we evaluated true, mixed, and fake news as determined by fact-checking organizations, such as Snopes, FactCheck, PolitiFact, and Poynter.

Analyzing social media data can be less biased than conducting public surveys because populations can be more diverse than the respondents to the survey. Indeed, social media analysis can capture more nuanced aspects of people's thoughts and feelings than a survey. Communication via social media platforms can be fake or real. As a result, we used machine learning algorithms, including the Passive-Aggressive Classifier, Decision Tree Classifier, and

AdaBoost Classifier, to identify 210,000 fake and real Tweets associated with five countries during the COVID-19, namely Australia, Singapore, Republic of Korea (i.e., South Korea), the United Kingdom, and the United States. We employed natural language processing and text mining techniques to extract linguistic, physical-psycho-social patterns. We considered community wellbeing and community capital as two critical components to measure community resilience during the COVID-19, where fake and real Tweets measure each component under the given countries. We assessed community wellbeing in terms of mental, physical, and social wellbeing.

According to our findings, social, family, and work-related languages (i.e., representing social wellbeing) extracted from real Tweets typically increase over time, whereas those from fake Tweets do not. In addition, people perceived up to 80% higher community resilience and community capital in real Tweets than in fake Tweets. On the other hand, people perceived up to 40% higher community wellbeing in fake Tweets than in real Tweets. Fake Tweets do not always spread negative information. They can disseminate positive information that is not true but still can mislead people's beliefs and actions according to their misbeliefs. We found the differences in community resilience between real and fake Tweets are 0.04, 0.18, 0.17, 0.07, and 0.05 under Australia, Singapore, the Republic of Korea, the United Kingdom, and the United States, respectively. While fake Tweets had a significant impact on Singapore and the Republic of Korea in the early time of the COVID-19, they significantly faded away as of June 2020.

While people's communications in Singapore and the United States via fake Tweets demonstrate positive indicators of community capital, their communication via real Tweets demonstrates negative indicators of and community capital, and vice versa. Except for the United States, both correlations of community wellbeing are positive for all countries. In our correlation analysis using Pearson's and Spearman's correlation coefficient, we found fairly high consistency in matching the trends observed in fake and real Tweets. In particular, Pearson's and Spearman's correlation coefficients for community resilience are positive under all the five countries.

Using the second framework, we analyzed community resilience (CR) during the COVID-19 pandemic in the US from Feb. 2020 to Jun. 2021 based on both news articles and Tweets in social media. We measured CR based on two main dimensions developed in this thesis: community wellbeing (CW) and resource distribution (RD). We also developed four different dimensions to measure RD: economic resilience, institutional resilience, infrastructural resilience, and community capital. We provided the output-oriented and capacity-based resilience analyses for various types of news and Tweets and investigated their general trends and relationships. In addition, we evaluated community resilience in terms of the meantime to absorption, community non-functioning, and recovery under various critical community functionality thresholds that determine the deadlock of community failure.

This research have the following limitations:

- There are no comparable works with which to compare the results of this work. Future studies can address the issue of comparative validation with other community resilience indices.

- Because a community can be viewed regionally, it can refer to a specific place. We regard the country as a community and place a greater emphasis on developing measurements of community resilience by examining the influence of various sorts of Tweets and news. As a result, we overlooked the network's effect on community resilience. The analysis of community resilience at the network level can be addressed in future work.

- To determine which Tweets are fake and which are real, we applied machine learning classifiers. However, we lacked a reference point against which to compare the result and assess their goodness. Thus, future work should focus on confirming the labels identified by machine learning classifiers using human expert reviews.

To sum up, we believe this work provides valuable insights in measuring community resilience using social media information and its relationships between various types of news articles and Tweets. Our findings and analysis of the correlations show that analyzing social media information can be less biased than public surveys because populations can be more diverse than survey participants in national surveys. In addition, more granularity of people's thoughts, moods, and feelings can be more appropriately captured from news and Tweets analyses than the national survey.

Policymakers can use the findings and insights gleaned from the presented analysis of social media data to assess the current state of community and society more accurately. Furthermore, they can find useful observations in this study to better prepare for the next pandemic. This method is not only applicable to the COVID-19, but it is also applicable to other types of disasters. Researchers, policymakers, non-governmental organizations (NGOs), governments, and engineers can easily use the proposed approach to assess the resilience of any community. Furthermore, the findings may help better resource planning and recovery response to the next pandemic or disaster. Furthermore, we can make better predictions about the social behavior of various communities. Using our findings, scholars can create new tools, such as a multi-agent-based model, to address the community's resilience. We hope this work can provide promising directions for policy decision-makers to efficiently and effectively recover from COVID-19.

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Appendices

Appendix A

Literature Review on Information-Processing Behavior, Fake and True News Propagation, Bias, and Risk Perception

A.1 Information-Processing Behavior

People have two inherent informational behaviors, information-seeking, and information-sharing behavior. When people feel fear and the ambiguity of their situation is raised, they need to seek information through mass media platforms and news resources. They are highly prone to share whether fake or authentic information they believe in.

Information seeking: a user has an inherent nature to seek information. There are two various types of people in terms of information-seeking behavior. These consist of the Need for cognition (NFC) and the Need for Cognitive Closure (NFCC) [1]. In another type of classification, we can put people in two different categories, i.e., an Open-minded agent and a Close-minded agent. NFC refers to the information process of a person who seeks more information with effortful consideration until the uncertainty is substantially reduced (slow

[1]The word need denote an individual's desire to seek information

decision). NFC moderate of the agents' bias correspondence bias [2]. The agents with Low NFC tend to show more heuristic bias (Halo effect) [3] due to mental shortcuts compared to the ones with high NFC [127]. Conversely, people with high NFC have bias obtained by high elaboration. In addition, NFC is negatively associated with social anxiety and fear. On the other hand, NFCC is the information process of a person who wants to simplify information and quickly reach a conclusion (quick decision). The high NFCC induces the ability to forecast the situation and to act based on a strong bias. In addition, high NFCC are prone to use the simple cognition process and experience confirmation bias [4]. There is also another social psychical term as Need to Avoid Closure. The agent tends to avoid specific answers and information to an ambiguous situation and problem. Of note, NFC behavior can increase the ambiguity of the situation, while NFCC can induce a decrease in uncertainty in the short term. Each of these behaviors has its pros and cons, according to the situation of the agent.

A.2 Fake and True News Propagation

Fake news is a type of news containing false information propagated by malicious entities through traditional news media, fake news websites, and New social technologies. Fake news can be made by anyone, and anyone can be exposed to fake news in the era of big data. Half of the people report that they are exposed to fake news on their social media at least once a day [128]. False information diffuses extensively faster and farther than the true information

[2]Is related to the situation that people tend to assess the situation or other people's behavior based on internal factors disregarding external factors

[3]These people are prone to absorb stereotypes, fake news, and rumors

[4]When a person experience confirmation bias means that one tends to interpret and make a conclusion from the information in such a way that they are in line with her/his preconceptions and prejudgment.

[21]. Fake news, identified as a global threat, have a various detrimental consequence on society. Fake news misguides the political and social activities of people and makes people lose their trust in mass media platforms. Fake news can make fear, Racist ideas, Bullying and violence against innocent people, and Democratic impacts. The fake news during events, e.g., pandemics, can make the situation even worse. Half of the UK adults face fake News regarding COVID-19 during the epidemic [129]. The people by getting fake information during a pandemic can make a wrong decision, or they are not able to make an appropriate decision to overcome the situation. That makes further losses during the pandemic. Wardle identifies seven types of fake news, i.e., satire or parody, false connection, misleading content, false context, impostor content, manipulated content, and fabricated content [130]. Fake news is often more novel than true information and usually is regarding sensational topics. Fake information typically induces negative feelings such as fear, disappointment, disgust, and annoyance, while real news stirs up positive emotions such as joy, sadness, and trust [21]. Official accounts, e.g., governmental or mass media agencies, release true reports. During a disaster, various types of news, whether fake or real news, are propagated. We assume that both fake news and real news can be negative or positive. Hence, we can put them in 4 categories as follows: *A-Fake news is positive*: Although fake news can be positive or negative, it always induces the inverse result that is not ideal behavior. Fake news makes the wrong fear or wrong happiness that is not true in the real world. We assume fake news is positive during the disaster. It means that to reduce the level of fear of people. Therefore, they do not feel that they are in danger while they are in danger in reality. It makes them face different types of losses.

A variety of models are proposed to model fake news and Rumer propagation in computational network science. Fake news model includes DK model, MK model, SIR, SHIR, SIRaRu model, the Dynamic 8-state ICSAR model, to name a few. In addition, mean-field equations, Lie algebraic approach is used in complex social dynamics models [131]. These models can be node-based or network-based. In these models, the degrees of the nodes can be static or dynamic. DK model includes three different classes, i.e., Ignorants, Spreaders, and Stiflers. Tambuscio et al.[20] consider fake news as virus. The distinguished difference between fake news diffusion and epidemic is related to subjective judgment. In fake news diffusion, subjective judgment, bias, and knowledge are vital while they are not considered in epidemic models [131]. The infection in the epidemic model is based on a passive process. In fake news propagation, an individual can quit the fake news diffusion in any state based on her subjective judgment. Zhu et al.[131] use the Susceptible–Hesitated–Infected–Removed (SHIR) fake news diffusion model. These classes are ignorant (S), hesitator (H), spreader (I), and stifler (R). In an ignorant state, individuals are not affected by fake news. In a hesitator state, individuals are affected by fake news while they are not effective in spreading fake news. In the spreader state, individuals spread fake news. In a stifler state, an individual's state is changed by fake news due to subjective judgment. The topology of the network is considered by Zhu et al.[131]. Vosoughi et al.[21] classify the false and correct information by using six independent fact-checking organizations. To model the propagation of fake news, one can use the opinion model known as Subjective Logic. Cho et al. [132] use an opinion model together with the SIR epidemic model for the propagation of fake news under uncertainty over time. Each opinion consists of the level of belief, disbelief, and uncertainty. This model allows the transition from any state to any state based on one's opinion status.

A.3 Bias

Epidemics such as the outbreak of coronavirus disease 2019 (COVID-19) influence public health. It raises the level of fear and negative emotion of people. Consequently, some people are likely to have stigma and bias toward other people, communities, and even nations. For example, prejudice and discrimination happen toward Asian descent during the outbreak of COVID-19 . Understandably, there is no difference between Asian people in the US and people from other nations in terms of the potential to get affected by COVID-19. In the case of COVID-19, individuals of Asian descent, individuals who had a trip, and emergency responders may experience stigma and bias. This behavior influence both the mental and physical health of Stigmatized people [133]. Of note, people tend to have confirmation bias. It means that people give more credit to news to support their existing beliefs.

A.4 Risk Perception

A critical factor in preventing the further spread of the virus and controlling the situation during the epidemic is to identify the risk. In other words, people must know that they are in danger during outbreaks of viruses[134]. It makes them follow policy and strategy to prevent putting them in further danger and make the situation worse. Besides, border screening, quarantine, isolation, closing schools/restaurants, postponing conferences, mask-wearing are examples of intervention strategies [135].

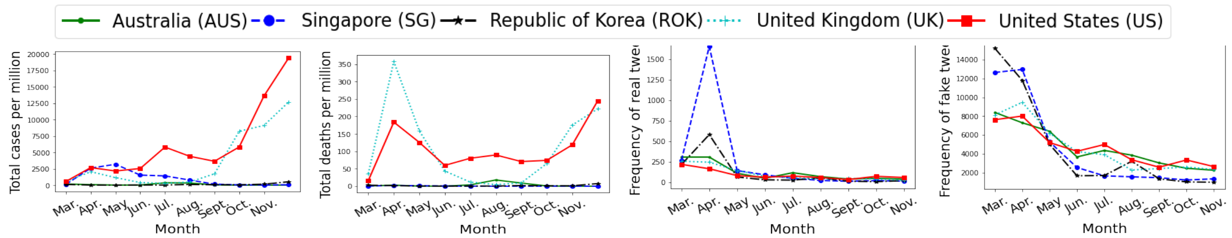
Appendix B

Supplementary Material for Analyzing Community Resilience of Australia (AUS), Singapore (SG), Republic of Korea (ROK), the United Kingdom (UK), and the United States (US)

B.1 Experimental Results Without Using Fitting Functions

In the main thesis, in order to capture more clear trends of the overall results, we used fitting functions for our analysis. In this section, we show the actual curves observed in our conducted experiments.

Fig. B.1 displays the total numbers of COVID-19 infection cases and deaths per million population and the frequencies of fake and real Tweets for the five countries (i.e., AUS, SH,



(a) Total infections per million (b) Total deaths per million (c) Frequency of real Tweets (d) Frequency of fake Tweets

Figure B.1: Total numbers of infections per million, total numbers of deaths per million, the frequency of fake Tweets, and the frequency of real Tweets for the five countries during Mar.-Nov. 2020.

ROK, UK, and the US) during the period of Mar.-Nov. 2020.

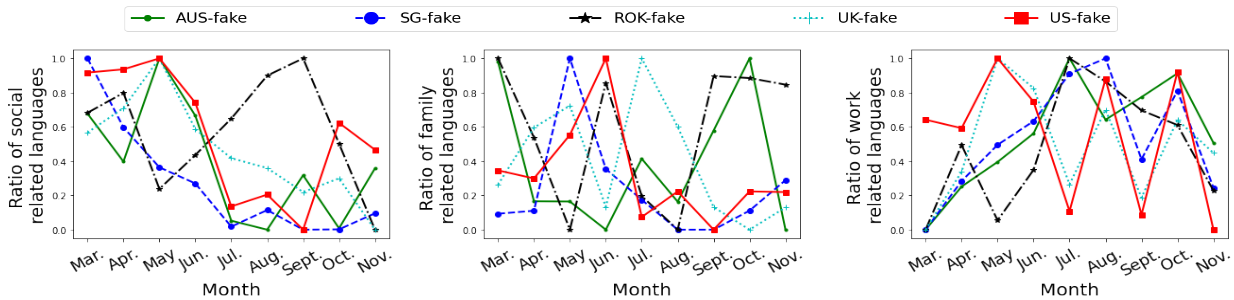
Fig. B.2 shows the three aspects of social wellbeing, which represent the extent of language uses related to social, family, and work features in LIWC under real and fake Tweets for the five countries during the given period.

Fig. B.3 shows the three aspects of community wellbeing in terms of mental, physical, and social wellbeing for the five countries during the same period.

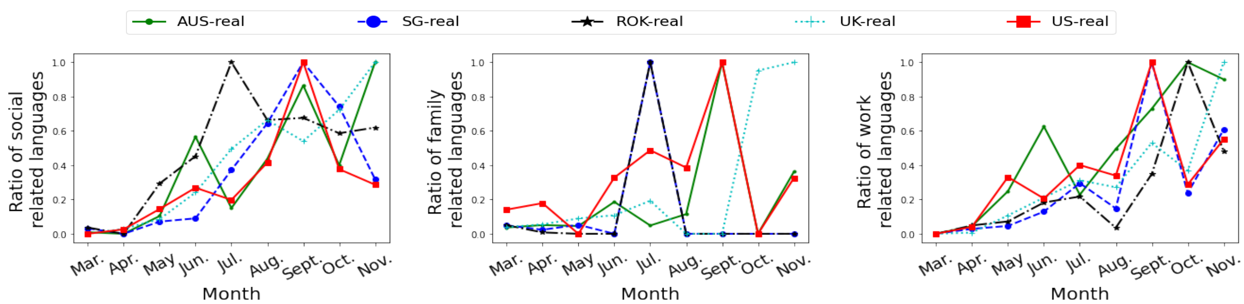
Fig. B.4 shows CW, CC, and CR using fake and real Tweets for the five countries during the same period.

B.2 Overall Capacity-based Resilience Measurements

Table B.1 summarizes the capacity-based measurements of community mental wellbeing, physical wellbeing, social wellbeing (consisting of social, family, and work-related degrees), community wellbeing, community capital, and community resilience as measured by real and fake Tweets under the five countries.



(a) Social network features from fake Tweets.
(b) Family features from fake Tweets.
(c) Work features from fake Tweets.

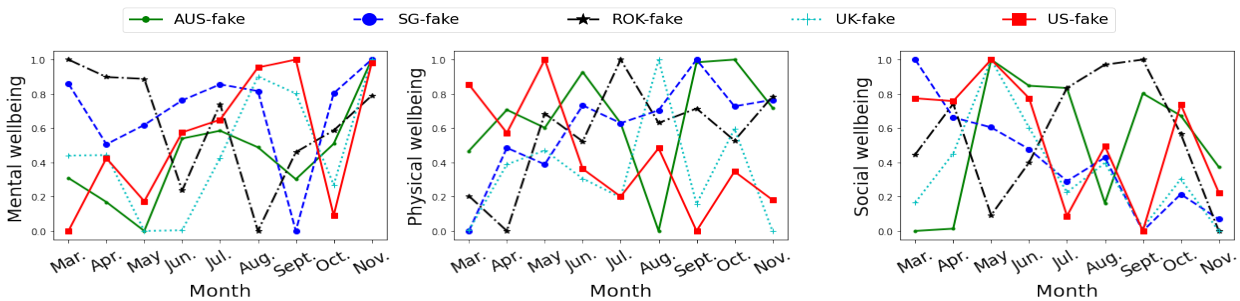


(d) Social network features from real Tweets.
(e) Family features from real Tweets.
(f) Work features from real Tweets.

Figure B.2: Measuring social wellbeing in terms of social network, family, and work features in LIWC using real and fake Tweets for the five countries during the period of Mar.-Nov. 2020.

Table B.1: Summary of the Capacity-Based Value of Resilience-Related Metrics

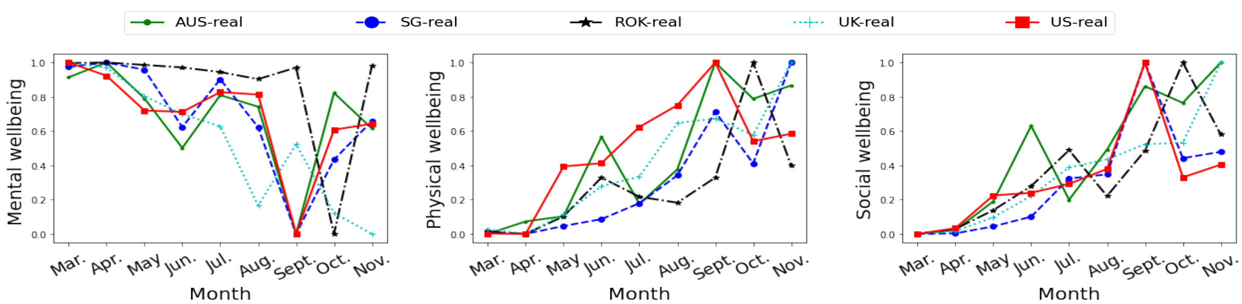
CR indexes	Countries	AUS		SG		ROK		UK		US	
	Label (Real/Fake)	Real	Fake	Real	Fake	Real	Fake	Real	Fake	Real	Fake
CW	Mental wellbeing	0.69	0.43	0.69	0.69	0.86	0.62	0.55	0.48	0.69	0.54
	Physical wellbeing	0.44	0.67	0.31	0.60	0.29	0.56	0.41	0.35	0.48	0.44
	Social wellbeing	0.46	0.52	0.30	0.42	0.36	0.56	0.36	0.35	0.32	0.54
SW	Social	0.39	0.39	0.36	0.27	0.48	0.58	0.42	0.46	0.30	0.56
	Family	0.20	0.39	0.13	0.24	0.12	0.58	0.27	0.40	0.32	0.33
	Work	0.47	0.56	0.28	0.53	0.27	0.48	0.31	0.49	0.35	0.55
Community wellbeing		0.53	0.54	0.43	0.57	0.50	0.58	0.44	0.39	0.50	0.51
Community capital		0.51	0.42	0.68	0.18	0.77	0.35	0.63	0.53	0.56	0.65
Community resilience		0.52	0.48	0.56	0.38	0.64	0.47	0.53	0.46	0.53	0.58



(a) Mental wellbeing from fake Tweets.

(b) Physical wellbeing from fake Tweets.

(c) Social wellbeing from fake Tweets.

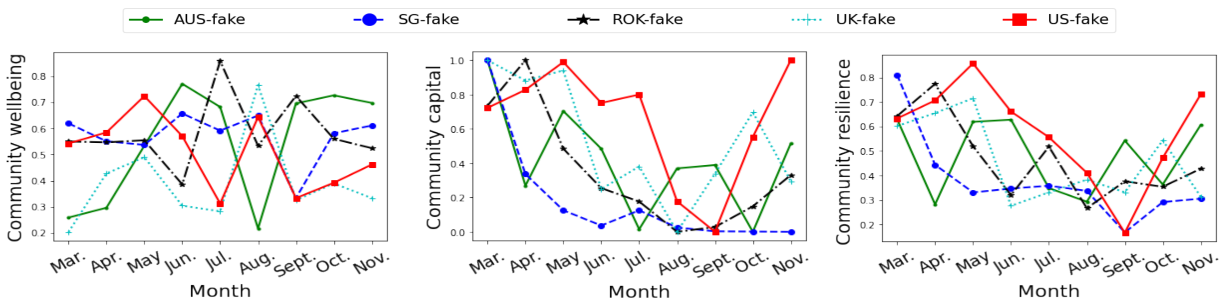


(d) Mental wellbeing from real Tweets.

(e) Physical wellbeing from real Tweets.

(f) Social wellbeing from real Tweets.

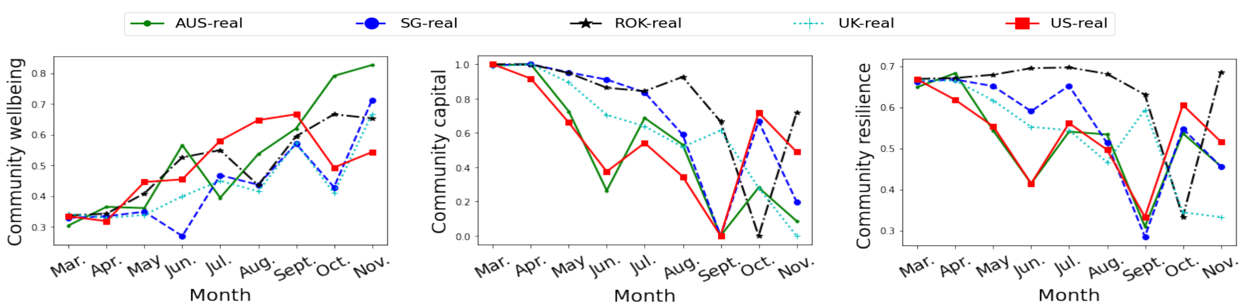
Figure B.3: Measuring community wellbeing in terms of mental, physical, and social wellbeing using real and fake Tweets for the five countries during the period of Mar.-Nov. 2020.



(a) Community wellbeing from fake Tweets.

(b) Community capital from fake Tweets.

(c) Community resilience from fake Tweets.



(d) Community wellbeing from real Tweets.

(e) Community capital from real Tweets.

(f) Community resilience from real Tweets.

Figure B.4: Community wellbeing, community capital, and community resilience measured based on COVID-19 related real and fake Tweets for the five countries during Mar.-Nov. 2020.

Appendix C

Supplementary Material for Analyzing Community Resilience Based on Community Wellbeing and Resources Distribution

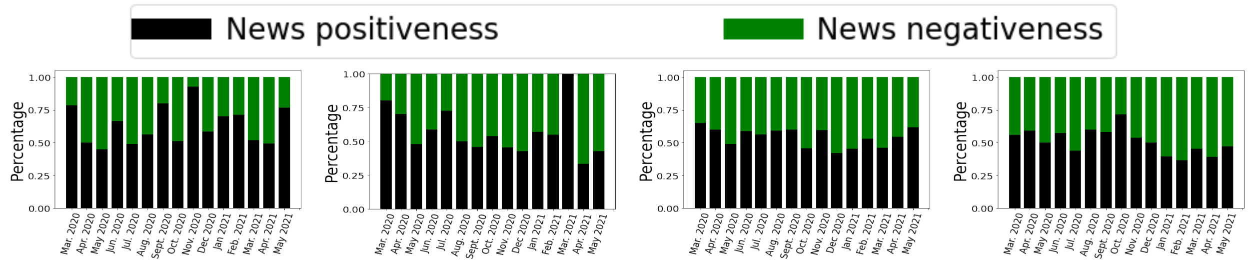
C.1 Additional News Analysis

Fact-checking organizations, including Snopes, Politifact, and Factcheck, provide information such as sources, keywords, subject, issue, and misconceptions for each news. Specifically, Snopes provides the source and related keywords for each news. Snopes also provides the subject of each news. Factcheck includes information about issues and misconceptions for each news. By collecting all of this information and cleaning them, we measure 1-gram and 2-grams, as shown in Table C.1. This table shows sources, keywords, subjects, issues, and misconceptions for real, mixed, and fake news.

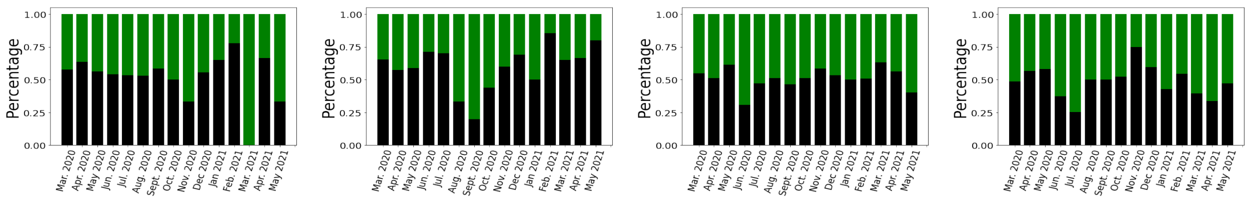
Fig. C.1 plots the positive and negative sentiments of the news texts for real, mixed, and fake news collected by each fact-checking organization for Jan. 2020 – Jun. 2021. We show the results related to each of real, mixed, and fake news from Snopes. We provide the result

Table C.1: 1-gram and 2-grams of sources, keywords, subject, issue, and misconceptions of Various Types of News Collected for Jan. 2020 – Jun. 2021.

Source	Info	1-grams (number)	2-grams (number)
Politifact (True)	Source	facebook (11), biden (7), image (3), toomey (3), Trump (3)	facebook posts (11), joe biden (7), pat toomey (3), donald trump (3), tony evers (3)
	Key words	coronavirus (86), health (42), public (21), wisconsin (19), facebook (14)	wisconsin coronavirus (18), public health (17), coronavirus facebook (9), carolina coronavirus (9), new york (8)
Politifact (Mixed)	Source	facebook (16), biden(7), trump (5),mandy (2), ron (2)	facebook posts (16), joe biden (7), donald trump (5), mandy cohen (2), ron de (2)
	Key words	coronavirus (67), facebook (29), health (28), public (21), budget (8)	public health (18), coronavirus facebook (16), health coronavirus (9), wisconsin coronavirus (8), carolina coronavirus (7)
Politifact (False)	Source	facebook (133), trump (38), instagram (20), bloggers (18), biden (11)	facebook posts (133), donald trump (38), instagram posts (20), joe biden (11), viral image (10)
	Key words	coronavirus (366), facebook (272), health (190), public (65), donald (38)	coronavirus facebook (131), health facebook (86), public health (64), health coronavirus (30), coronavirus donald (30)
Snopes (True)	Subject	politics (101), medical (36), fauxtography (20), business (14), entertainment (14), viral (5), phenomena (5), crime (5), history (5), health (5)	politics politics (42), politics medical (18), medical politics (16), fauxtography politics (15), politics fauxtography (12), medical medical (8), business politics (6), viral phenomena (5), politics entertainment (5), entertainment politics (4)
Snopes (Mixed)	Subject	politics (67), medical (24), business (6), health (4), fauxtography (3), food (2), media (2), matters (2), crime (2), critter (2)	politics politics (43), medical politics (14), politics medical (9), medical medical (8), politics business (3), business medical (2), politics fauxtography (2), fauxtography politics (2), media matters (2), politics crime (2)
Snopes (False)	Subject	politics (153), medical (70), fauxtography (28), entertainment (14), junk (13), news (13), business (12), viral (10), phenomena (10), technology (8)	politics politics (73), politics medical (33), medical politics (24), medical medical (19), fauxtography politics (14), junk news (13), politics fauxtography (12), viral phenomena (10), medical fauxtography (6), news medical (5)
Factcheck	Issue	coronavirus (389), covid (364), vaccine (42), masks (26), face (25)	covid 19 (364), coronavirus covid (246), novel coronavirus (125), coronavirus coronavirus (79), face masks (25)
	Miscon-ceptions	vaccination (45), safety (25), virulence (12), sars (12), cov (12)	vaccination safety (25), virulence of (12), sars cov (12), distortions of (11), of science (11)



(a) Real news– Snopes (b) Mixed– Snopes (c) Fake news– Snopes (d) Fake– Factcheck



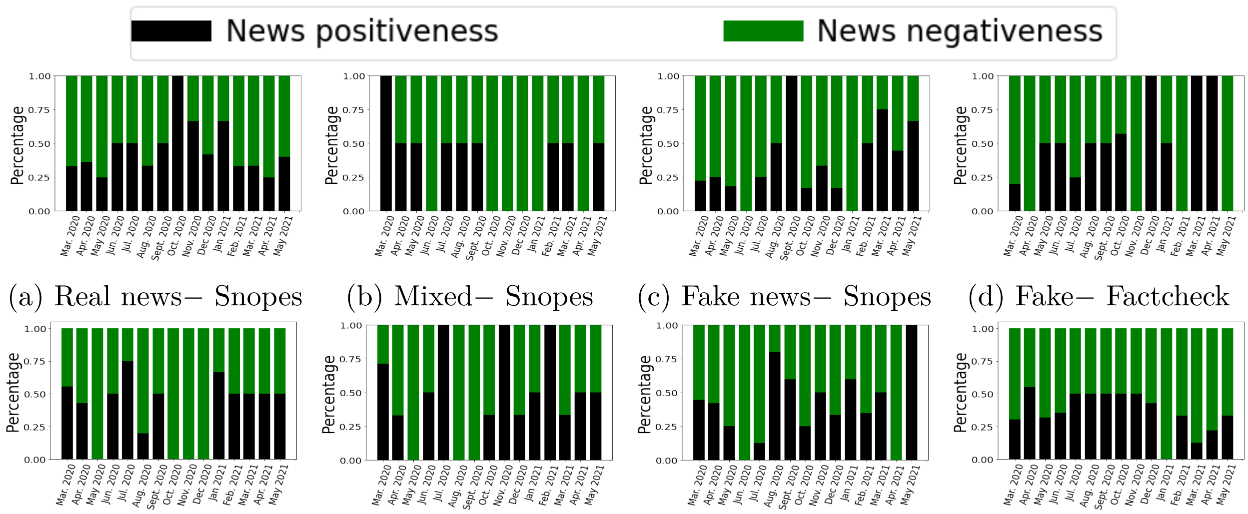
(e) Real– Politifact (f) Mixed– Politifact (g) Fake – Politifact (h) Fake – Poynter

Figure C.1: The positiveness and negativeness of news texts about the COVID-19 for each fact-checking organization for Jan. 2020 – Jun. 2021 as follows: 1) Snopes: news texts of real, mixed, and fake news; 2) Factcheck: news texts of fake news; 3) Politifact: news texts of real, mixed, and fake news; and 4) Poynter: news texts of fake news.

related to fake news from Factcheck. We also demonstrate the results related to each of real, mixed, and fake news from Politifact and related to fake news from Poynter. From the analysis, real news has more positive sentiments than fake news.

Fig. C.2 plots the positive and negative sentiments of the news titles for various types of news collected by each fact-checking organization for Jan. 2020 – Jun. 2021. We showed the following results: 1) Snopes: news titles of real, mixed, and fake news; 2) Factcheck: news titles of fake news; 3) Politifact: news titles of real, mixed, and fake news; and 4) Poynter: news titles of fake news. Based on this analysis, we found that the title of all types of news is more negative than the texts of news.

Fig. C.3 illustrates the word cloud associated with the news texts for various types of news collected by each fact-checking organization for Jan. 2020 – Jun. 2021. Specifically, we show the word cloud for the following data-set: 1) Snopes: news texts of real, mixed, and fake news; 2) Factcheck: news texts of fake news; 3) Politifact: news texts of real, mixed, and



(a) Real news– Snopes (b) Mixed– Snopes (c) Fake news– Snopes (d) Fake– Factcheck

(e) Real– Politifact (f) Mixed– Politifact (g) Fake– Politifact (h) Fake– Poynter

Figure C.2: The positiveness and negativeness of news titles about the COVID-19 for each fact-checking organization for Jan. 2020 – Jun. 2021 as follows: 1) Snopes: news titles of real, mixed, and fake news; 2) Factcheck: news titles of fake news; 3) Politifact: news titles of real, mixed, and fake news; and 4) Poynter: news titles of fake news.

fake news; and 4) Poynter: news texts of fake news.

Fig. C.4 illustrates the word cloud associated with the news titles for various types of news collected by each fact-checking organization for Jan. 2020 – Jun. 2021. We showed the word cloud for the following data-set: 1) Snopes: news titles of real, mixed, and fake news; 2) Factcheck: news titles of fake news; 3) Politifact: news titles of real, mixed, and fake news; and 4) Poynter: news titles of fake news.

C.2 Additional Mental and Physical Wellbeing Assessment Based on News Titles

From Feb. 2020 to Jun. 2021, Fig. C.5 depicts the normalized degree of mental and physical wellbeing as measured by real, mixed, and fake news titles as well as real and fake Tweets.

(a) Real news– Snopes (b) Mixed– Snopes (c) Fake news– Snopes (d) Fake– Factcheck

(e) Real– Politifact (f) Mixed– Politifact (g) Fake – Politifact (h) Fake – Poynter

Figure C.3: Word cloud for the news texts of real, mixed, and fake news for each fact-checking organization for Jan. 2020 – Jun. 2021.

C.3 Output-Oriented Resilience Assessment

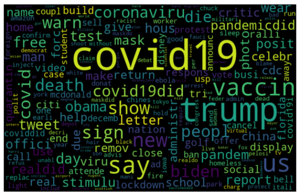
Fig. C.6 illustrates the degree of community wellbeing, community capital, economic resilience, institutional resilience, infrastructure resilience, and community resilience measured by the news titles (i.e., real, mixed, and fake) and Tweets (i.e., real and fake) collected for Feb. 2020 – Jun. 2021.

Fig. C.7 illustrates the Quantile-Quantile (Q-Q)-plot for community mental wellbeing in relation to various news types (i.e., real, mixed, or fake) and Tweet types (i.e., real or fake).

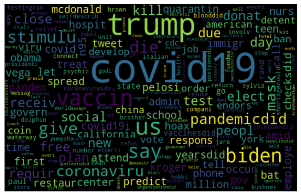
Fig. C.8 illustrates the Quantile-Quantile (Q-Q)-plot for community physical wellbeing in relation to various news types (i.e., real, mixed, or fake) and Tweet types (i.e., real or fake).

Fig. C.9 illustrates the Quantile-Quantile (Q-Q)-plot for community wellbeing in relation to various news types (i.e., real, mixed, or fake) and Tweet types (i.e., real or fake).

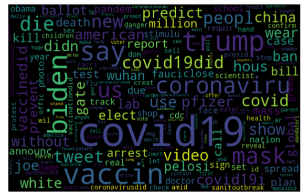
Fig. C.10 illustrates the Quantile-Quantile (Q-Q)-plot for community capital in relation to various news types (i.e., real, mixed, or fake) and Tweet types (i.e., real or fake).



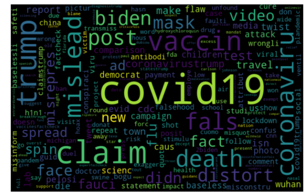
(a) Real news– Snopes



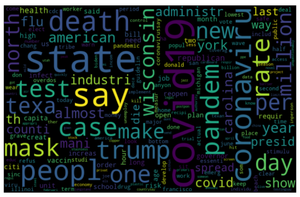
(b) Mixed– Snopes



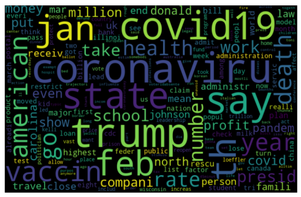
(c) Fake news– Snopes



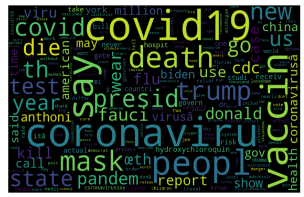
(d) Fake– Factcheck



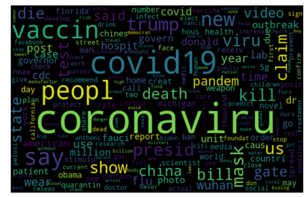
(e) Real– Politifact



(f) Mixed– Politifact



(g) Fake– Politifact



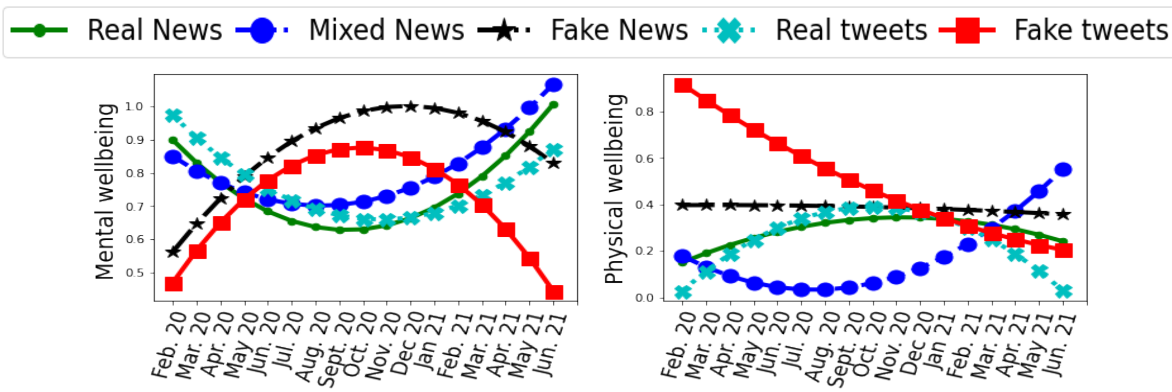
(h) Fake– Poynter

Figure C.4: Word cloud for the news titles of real, mixed, and fake news for each fact-checking organization for Jan. 2020 – Jun. 2021.

Fig. C.11 illustrates the Quantile-Quantile (Q-Q)-plot for economic resilience in relation to various news types (i.e., real, mixed, or fake) and Tweet types (i.e., real or fake).

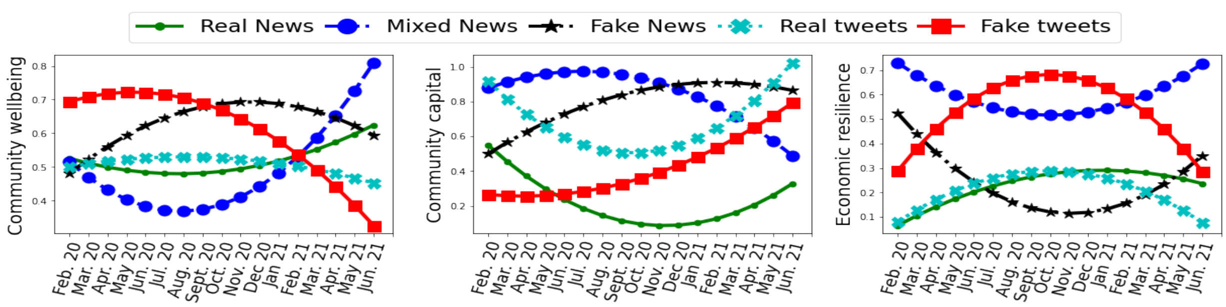
Fig. C.12 illustrates the Quantile-Quantile (Q-Q)-plot for institutional resilience in relation to various news types (i.e., real, mixed, or fake) and Tweet types (i.e., real or fake).

Fig. C.13 illustrates the Quantile-Quantile (Q-Q)-plot for infrastructure resilience in relation to various news types (i.e., real, mixed, or fake) and Tweet types (i.e., real or fake).

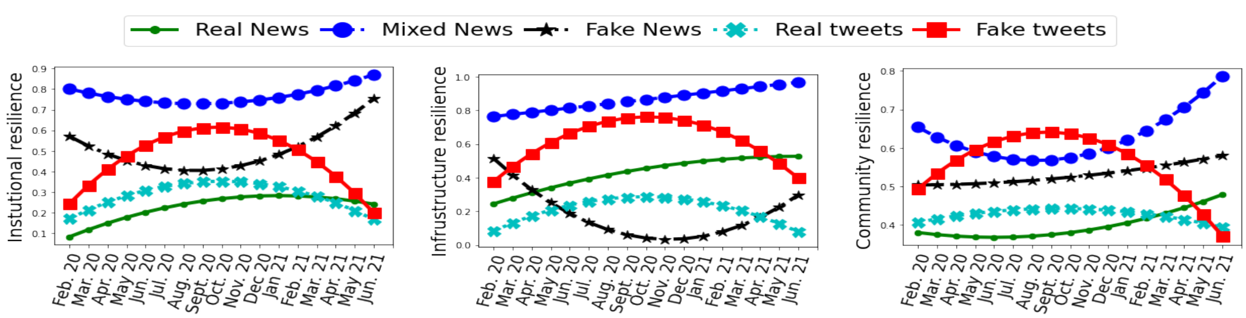


(a) Mental wellbeing (b) Physical wellbeing

Figure C.5: Measures of community wellbeing based on mental wellbeing and physical wellbeing by different types of news titles and Tweets.

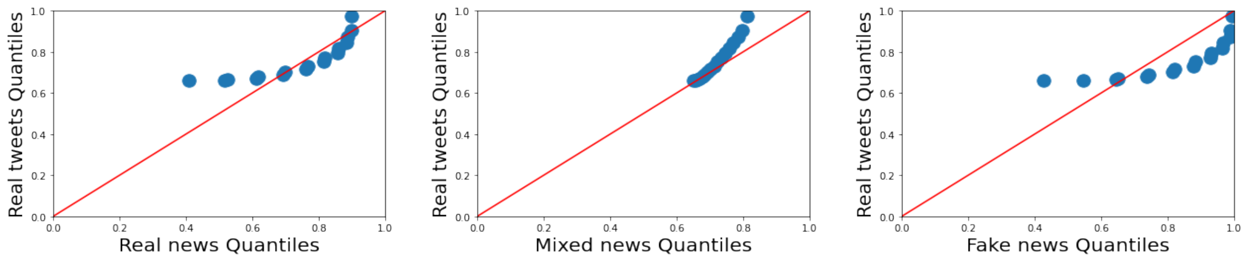


(a) Community wellbeing. (b) Community capital. (c) Economic resilience.

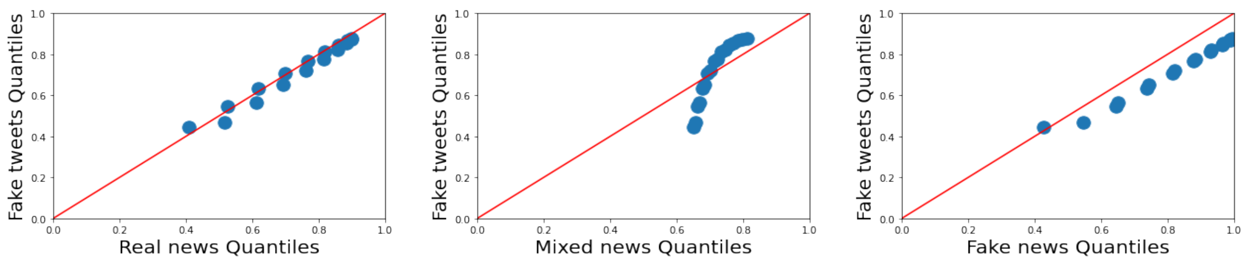


(d) Institutional resilience. (e) Infrastructure resilience. (f) Community resilience .

Figure C.6: Community wellbeing, community capital, economic resilience, institutional resilience, infrastructure resilience, and community resilience measured based on different types of news titles and Tweets for Feb. 2020–Jun. 2021.

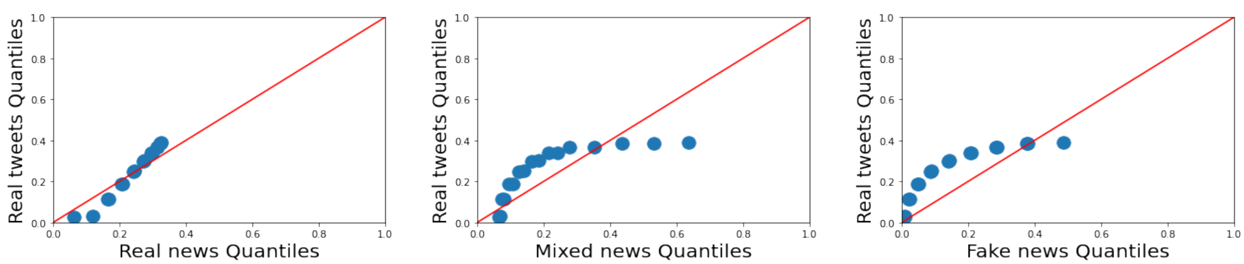


(a) Real Tweets vs. real news (b) Real Tweets vs. mixed news (c) Real Tweets vs. fake news

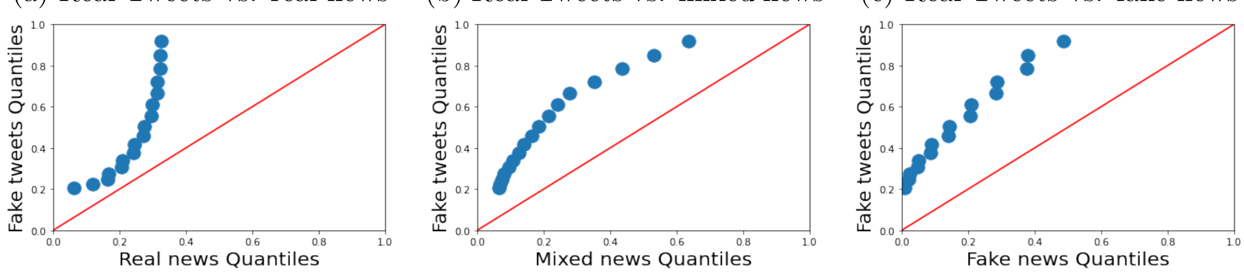


(d) Fake Tweets vs. real news (e) Fake Tweets vs. mixed news (f) Fake Tweets vs. fake news

Figure C.7: The Quantile-Quantile (Q-Q)-plot of news and Tweets used to measure community mental wellbeing where x-axis refers to the quantiles of real, mixed, or fake news and y-axis indicates the quantiles of real, fake, or all Tweets.

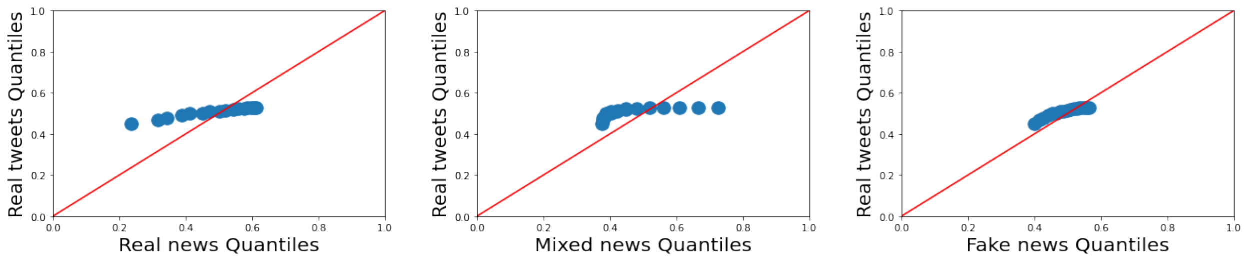


(a) Real Tweets vs. real news (b) Real Tweets vs. mixed news (c) Real Tweets vs. fake news

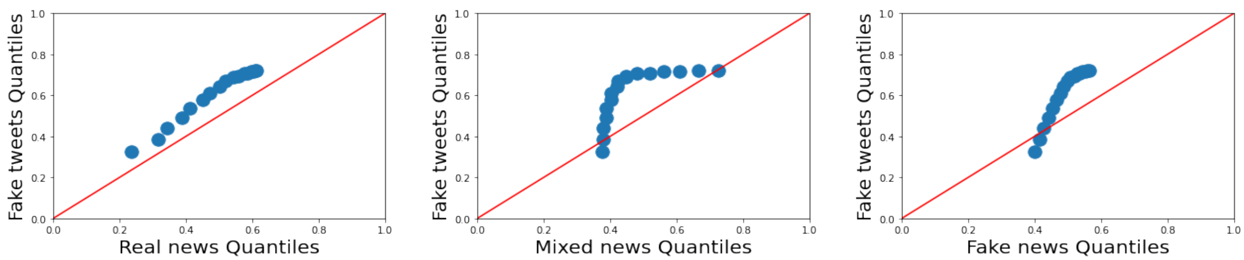


(d) Fake Tweets vs. real news (e) Fake Tweets vs. mixed news (f) Fake Tweets vs. fake news

Figure C.8: The Quantile-Quantile (Q-Q)-plot of news and Tweets used to measure community physical wellbeing where x-axis refers to the quantiles of real, mixed, or fake news and y-axis indicates the quantiles of real, fake, or all Tweets.

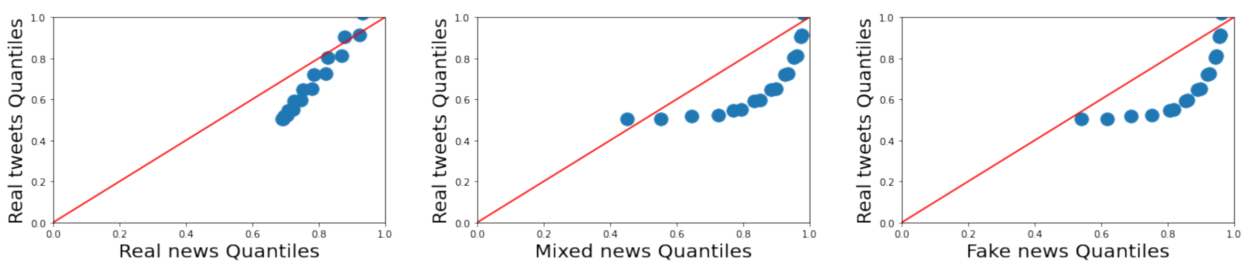


(a) Real Tweets vs. real news (b) Real Tweets vs. mixed news (c) Real Tweets vs. fake news

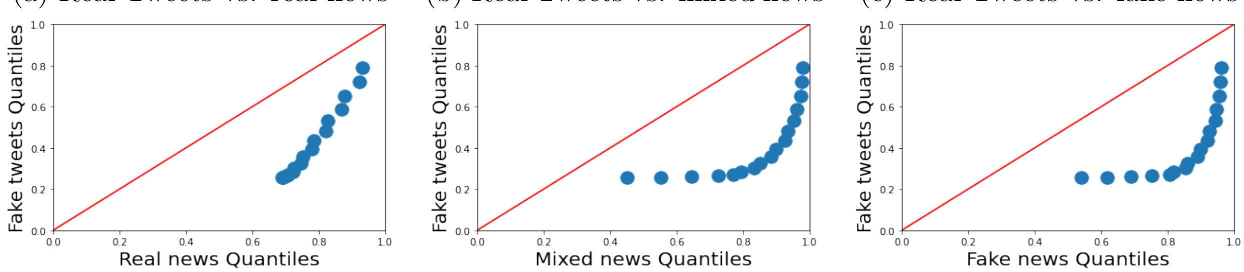


(d) Fake Tweets vs. real news (e) Fake Tweets vs. mixed news (f) Fake Tweets vs. fake news

Figure C.9: The Quantile-Quantile (Q-Q)-plot of news and Tweets used to measure community wellbeing where x-axis refers to the quantiles of real, mixed, or fake news and y-axis indicates the quantiles of real, fake, or all Tweets.

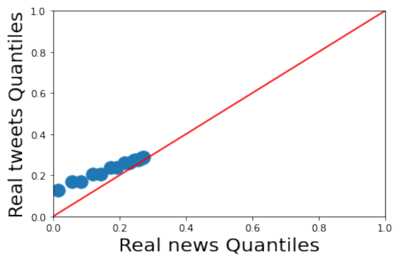


(a) Real Tweets vs. real news (b) Real Tweets vs. mixed news (c) Real Tweets vs. fake news

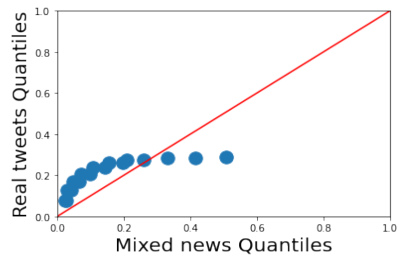


(d) Fake Tweets vs. real news (e) Fake Tweets vs. mixed news (f) Fake Tweets vs. fake news

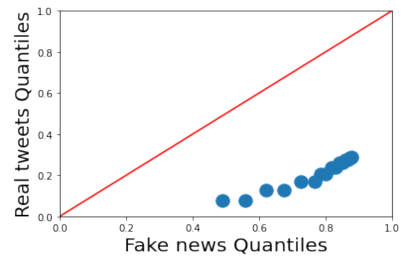
Figure C.10: The Quantile-Quantile (Q-Q)-plot of news and Tweets used to measure community capital where x-axis refers to the quantiles of real, mixed, or fake news and y-axis indicates the quantiles of real, fake, or all Tweets.



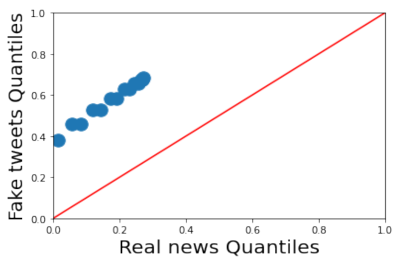
(a) Real Tweets vs. real news



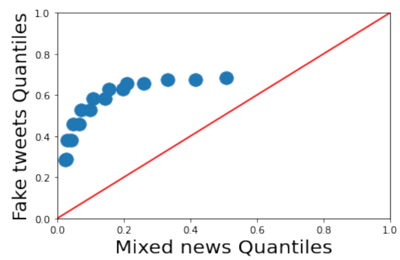
(b) Real Tweets vs. mixed news



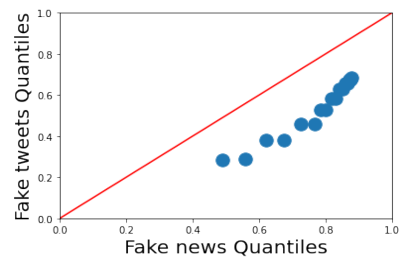
(c) Real Tweets vs. fake news



(d) Fake Tweets vs. real news

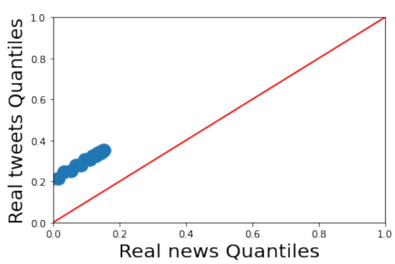


(e) Fake Tweets vs. mixed news

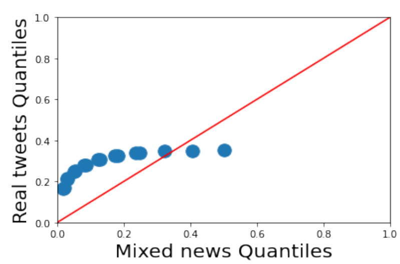


(f) Fake Tweets vs. fake news

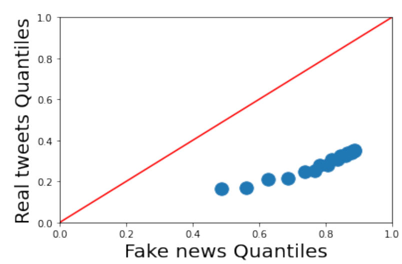
Figure C.11: The Quantile-Quantile (Q-Q)-plot of news and Tweets used to measure economic resilience where x-axis refers to the quantiles of real, mixed, or fake news and y-axis indicates the quantiles of real, fake, or all Tweets



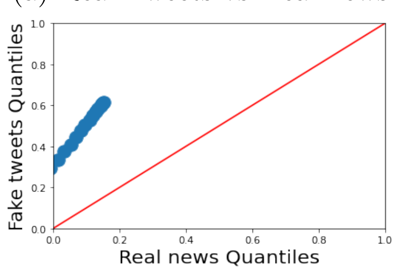
(a) Real Tweets vs. real news



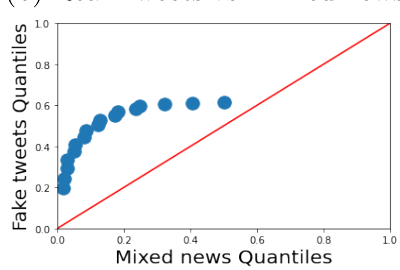
(b) Real Tweets vs. mixed news



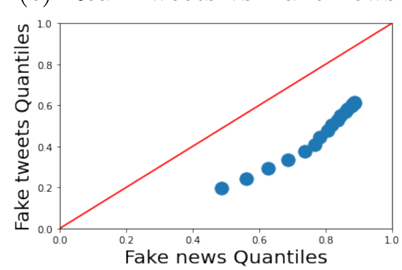
(c) Real Tweets vs. fake news



(d) Fake Tweets vs. real news

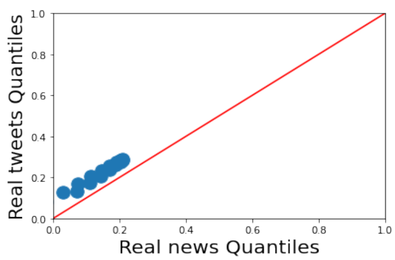


(e) Fake Tweets vs. mixed news

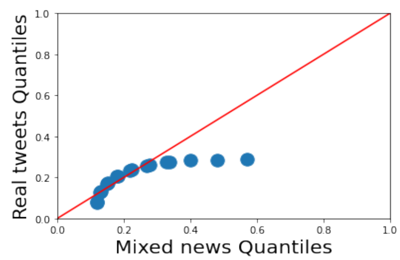


(f) Fake Tweets vs. fake news

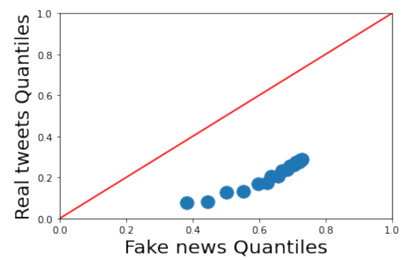
Figure C.12: The Quantile-Quantile (Q-Q)-plot of news and Tweets used to measure institutional resilience where x-axis refers to the quantiles of real, mixed, or fake news and y-axis indicates the quantiles of real, fake, or all Tweets.



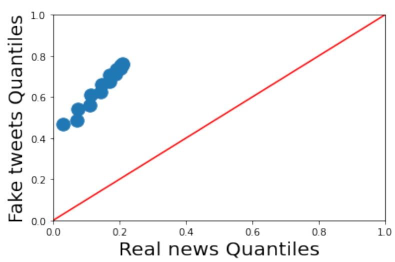
(a) Real Tweets vs. real news



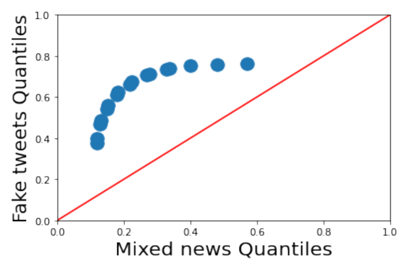
(b) Real Tweets vs. mixed news



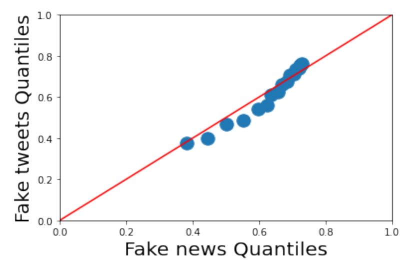
(c) Real Tweets vs. fake news



(d) Fake Tweets vs. real news



(e) Fake Tweets vs. mixed news



(f) Fake Tweets vs. fake news

Figure C.13: The Quantile-Quantile (Q-Q)-plot of news and Tweets used to measure infrastructure resilience where x-axis refers to the quantiles of real, mixed, or fake news and y-axis indicates the quantiles of real, fake, or all Tweets