Journal of Computational Social Science (2023) 6:1001–1032
https://doi.org/10.1007/s42001-023-00220-z

RESEARCH ARTICLE

Social media-based social–psychological community resilience analysis of five countries on COVID-19

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Received: 9 November 2022 / Accepted: 12 July 2023 / Published online: 18 August 2023

Abstract

Community resilience (CR) has been studied as an indicator to measure how well a given community copes with and recovers from a given disaster. Social–psychological community resilience (SPCR) has been used as a basis to determine public policy directions based on priority. Although the impact of the COVID-19 has been serious all over the world and interferes every aspect of our daily life, some countries have handled this disaster better than others due to their different disaster management policies and perceptions about the disaster. In this work, we are interested in measuring and analyzing SPCR through social media information in five different countries which can reflect different disaster management policies and perceptions toward the COVID-19. In the literature, measuring SPCR has been discussed, but the key attributes have not been agreed upon. We propose to use two attributes for measuring SPCR, i.e., community wellbeing (CW) and community capital (CC), because social and psychological resilience can be the firm basis for a community to be restored and reinvented into the so-called *transformative community* to ensure sustainability in the future generation. We use Tweeter data and investigate how each country shows different trends of SPCR in response to real and fake tweets generated during a COVID-19 period using machine learning and text-mining tools. We employ tweets generated in Australia (AUS), Singapore (SG), Republic of Korea (ROK), the United Kingdom (UK), and the United States (US), during March–November 2020 and measure the SPCR of each country and its associated attributes for analyzing the overall trends. Our results show that ROK among the five countries in our study has the highest level in CW, CC, and the resulting SPCR on real tweets reflecting reality, a result that matches well with the fact that ROK is resilient to COVID-19 during March–November 2020. Further, our results indicate that SPCR on real tweets is up to 80% higher than SPCR on fake tweets, suggesting that a much stronger community resilience may be achieved on real tweets. Finally, our results show that there is a negative correlation between SPCR values on fake and real tweets overall when considering all the tweets of the five countries to derive the overall trends. However, for each country, we observe a different correlation, either positive or negative, depending on each country. This implies that there should be

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further investigation of analyzing SPCR by considering unique cultural and national characteristics of each country.

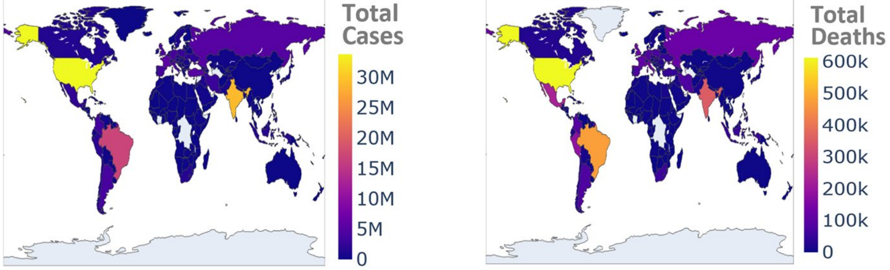
Keywords Applied computing · Psychology · Computing methodologies · Model verificationand validation · Social–psychological community resilience · Social media · Fake news · Real news · COVID-19 · Text mining · Data science · NLP (Natural language programming)

Introduction

Motivation

The outbreak of COVID-19 has impacted every aspect of our daily life. Naturally, numerous studies have addressed diverse COVID-19-related problems in social sciences, epidemiology, computational sciences, or medical sciences [54, 74]. COVID-19 has resulted in many losses, such as human deaths, economic losses, and health problems, in the majority of countries in the world. As shown in Fig. 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.

Disaster management has been studied in vulnerability, resilience, and sustainability research. Vulnerability indicates the pre-event traits representing the inherent quality of social systems that can potentially generate harms to the systems [11]. Adger [1] defined vulnerability as a function of being exposed to risks and the sensitivity of a system (e.g., people or places) to the risks. On the other hand, resilience refers to the post-event state representing the capability that a social system can adaptively respond to and recover from disasters Holling [23], including absorbing impacts and coping with disasters where adaptive capability, such as reorganizing, changing, or learning to effectively respond a disaster (or threat) [11]. Resilience to disasters has been studied to support sustainability of a social system. Sustainability



(a) Total infection cases

(b) Total death cases

Fig. 1 World COVID-19 total infection and death cases [80] refers to the ability of tolerating and overcoming damage, such as reduced performance or quality of a system without the help of outside resources [43]. Therefore, we are motivated to investigate the resilience of a nation as a community under a disaster, particularly COVID-19, as we are currently facing, as a driving force to build a sustainable social system.

Although the so-called 'community resilience' (CR) has been studied for several decades, there are no agreed-upon key attributes for measuring CR in the research community. Community resilience theory focuses on the ability of communities as a whole to adapt and recover from stressors. This theory recognizes that communities are complex systems made up of many different individuals and organizations, and that resilience depends on the interactions and relationships between these different actors. Community resilience theory also emphasizes the importance of leadership and governance structures in promoting resilience at the community level. Social resilience theory, on the other hand, focuses on the ability of individuals and social networks to adapt and cope with stressors, such as economic downturns or natural disasters. This theory emphasizes the importance of social networks and social support in promoting resilience, as well as the role of individual and collective agency in responding to and recovering from stressors. Social resilience theory and community resilience theory are closely related concepts, as they both aim to explain and enhance the ability of groups of people to cope with and recover from adversity.

Social–Psychological community resilience (SPCR) has been discussed along with a variety of attributes and partly measured and analyzed based on those attributes using survey-based social science methodologies. For example, during the COVID-19 period, various survey-based studies have been conducted to assess the psychological resilience (e.g., anxiety, depression, and stress) and quality of life in China [55, 76, 77], neuroscientific impacts (e.g., social and psychological) and emotional responses in the United Kingdom [24, 29], and socioeconomic resilience (e.g., ingenuity, empathy, and moral responsibility) in the US [28]. However, the sizes of samples are relatively small and the samples are often biased. In addition, information collected is limited to only questions answered. Further, to conduct a fairly valid experiment, it is 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.

To avoid the above issues in survey-based measurements of CR, our work takes social sensing-based methods [5, 13, 52, 66] for measuring CR. In addition, as discussed in Sect. 2.1, SPCR has been discussed based on several key attributes, including ecological, social, economic, institutional, infrastructure, and health or wellness [11, 67]. However, as the literature shows, it is not feasible to measure all the attributes to measure the overall SPCR with respect to time. In addition, recently, the importance of 'social resilience,' including human capital, social capital, and trust, has been realized as key components of the so-called *transformative resilience* [18]. That is, understanding people's perceptions about a disaster and their moods are highly critical as they can significantly influence the way they actually handle the disaster. Therefore, in this work, we focus on measuring *social–psychological community resilience* (SPCR) based on social media information (i.e., tweets) using text-mining tools. Particularly, we will analyze the overall trends of SPCR in response to both fake and real tweets generated during the COVID-19 period. We choose tweets, not news articles, as social media information to analyze SPCR for two reasons. First, tweets can better exhibit people's realistic characteristics. Second, the analysis of human informal languages can better capture their social and psychological resilience to deal with a disaster (e.g., COVID-19) [68]. In addition, we analyze SPCR using tweets in five different countries to examine how each country differently perceives SPCR, which may be influenced by its disaster management policy or unique national characteristics.

Research goal, contributions, and questions

The goal of this work is to measure social–psychological community resilience (SPCR) using social media information, such as tweets, including both fake and real (true) tweets generated during a COVID-19 period, and investigate the overall trends observed in the measured SPCR of five different countries. The **key contributions** are as follows:

- We propose two key attributes, namely, community wellbeing (CW) and community capital (CC) to measure SPCR. The reason is that CW indicates a community's mental and social wellbeing [12, 79], while CC indicates the degree of cooperation in a given community to reflect a community's value and cohesion [50]. Both CW and CC have not been considered before for measuring SPCR. Furthermore, our work is the first that measures SPCR using social media information based on these two attributes. While the disaster considered in this paper is COVID-19, the approach proposed is generally applicable to measure SPCR for other types of disasters.
- We present a novel method to assess SPCR 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 period, there has been no metric defined to capture SPCR of multiple countries using social media information such as tweets. To the best of our knowledge, we are the first that measures SPCR using real and fake tweets based on the concept of system resilience in the engineering domain [7] as a dynamic metric with respect to time.
- We conduct extensive comparative analysis of SPCR for five countries, including Australia (AUS), Singapore (SG), Republic of Korea (ROK or South Korea), the United Kingdom (UK), and the United States (US). We select these countries, because AUS, SG, and ROK are well-known as good examples of managing COVID-19 with fairly low infection and death cases, while UK and US have had hard times to handle COVID-19 cases. Through the analysis of SPCR using tweets, we discover that these countries have different perceptions toward COVID-19, which may influence the way they actually respond to the COVID-19 disaster.
- We analyze the linear and monotonic correlations between fake and real tweets in SPCR and its attributes using two correlation coefficients, namely, Pearson

and Spearman, and investigate the similarities between SPCR measured by real tweets and SPCR measured by fake tweets. In addition, we analyze the key differences of the correlations of SPCR measures in five different countries.

Our study will answer the following **research questions**:

(1) *What are the main trends observed in SPCR and our proposed key attributes for measuring SPCR (i.e., community wellbeing and community capital) and what are the implications of the trends observed for five different countries (i.e., AUS, SG, ROK, UK, and US) on COVID-19?*
(2) *What are the key differences and correlations between the SPCR measured on fake tweets and SPCR measured on real tweets?*
(3) *What are the key differences and correlations of the measured SPCR in five different countries when SPCR is measured on fake or real tweets?*

We conduct our study by assuming the following intuitions. First, real tweets can be used to better represent SPCR than fake tweets. Second, knowing a current situation with accurate information can lead people to make more rational decisions to handle a faced disaster, which is COVID-19 in this work. Although the scope of this work is limited to measuring and analyzing SPCR using tweets, the further investigation to prove the above as the hypothesis will be conducted in our future work.

Structure of the paper

The rest of this paper is organized as follows. Section 2 provides a brief overview about community resilience and sentiment analysis research using social media information. Section 3 describes the key attributes considered to measure social–psychological community resilience (SPCR) and the text-mining tools for data collection. Section 4 describes the tweets data used for experimental evaluation, the procedure of collecting data for measuring community wellbeing, community capital and SPCR, and experimental results with physical implications given. Section 5 concludes our paper with key findings and suggests future research directions.

Related work

In this section, we first survey existing works on community resilience and sentiment analysis research on COVID-19 using social media datasets. Then, we contrast and compare our work relative to these works.

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 [71, 72]. Note that community functionality is how well a community functions to provide a variety of vital services to its community residents [36, 69]. 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 [73]. 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) [7]. 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) [10], COmposite of Post-Event WELLbeing (COPEWELL) [36], United Nations Office for Disaster Risk Reduction (UNDRR) [65, 78], Disaster Resilience Of Place (DROP) [11], Community Disaster Resilience Index (CDRI) [41], Resilience Capacity Index (RCI) [17], and Resilience Analysis and Planning Tool (RAPT) provided by the Federal Emergency Management Agency (FEMA) [44, 51]. 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 [6, 10, 70]. Moreover, CR was measured based on the part of those attributes mainly using survey-based methods.

Gotham and Campanella [19] first proposed the concept of *transformative resilience* (TR) to extend the traditional concept of resilience into rebuilding a system, not just returning to a pre-disaster state or the status quo. Instead, TR refers to the ability of rebuilding a community with new relationships and new structures that can further sustain in the future. TR emphasizes the importance of a social network as the basis of building social capital to promote social, economic, and ecological diversity and self-reliance. As Granovetter [20] discussed in the concept of the 'strength of weak ties,' a large but trustworthy social network can play a critical role in establishing the coalitions with neighbors and other community institutions (e.g., schools or governments) and can increase flows of information and resources, ultimately leading to enhancing CR. Norris et al. [48] also stressed the importance of information and resources available through human and social capitals as the key factors to mitigate risk and inequality of resource distributions.

Giovannini et al. [18] discussed TR in the context of dealing with COVID-19. They discussed TR as the multidimensional concept of resilience by emphasizing transformation as well as prevention, preparation, protection, and promotion in measuring resilience. They also stressed the aspects of social and societal resilience (SSR) in addition to economic, environmental, and institutional resilience. The SSR is closely related to rebuilding human and social capitals and trust. In particular, they emphasized the importance of the societal mood and people's perceptions to maintain sustainability via SSR. In addition, Rippon et al. [57] considered the concept of TR in dealing with the COVID-19 pandemic based on support networks in terms of individuals with social networks, formal voluntary and community sector with infrastructure networks, and local systems with health and social services networks.

We summarize the key attributes of community resilience discussed in the literature in Table 1. The COVID-19 pandemic has had a significant impact on the social–psychological wellbeing of individuals and communities around the world. Community resilience, which refers to the ability of communities to adapt and recover from stressors, can play an important role in promoting social–psychological wellbeing during this time. Here are some ways that different dimensions of community resilience may be related to social–psychological wellbeing during the COVID-19 pandemic:

1. Social connectedness: Social connectedness is a key dimension of community resilience that refers to the strength and quality of social networks within a community [4, 40]. During the pandemic, social connectedness can help individuals feel less isolated and lonely, and provide a sense of support and belonging [47]. This can in turn promote social–psychological wellbeing.
2. Adaptive capacity: Adaptive capacity is another important dimension of community resilience, referring to the ability of a community to respond and adapt to change [39, 48]. During the pandemic, communities with high adaptive capacity may be better able to quickly mobilize resources and implement effective strategies to address the challenges posed by COVID-19 [28]. This can promote a sense of control and efficacy, which can in turn contribute to social–psychological wellbeing.
3. Leadership and governance: The leadership and governance structures within a community can also play an important role in promoting community resilience and social–psychological wellbeing [15, 81]. Effective leadership and governance can help coordinate responses to the pandemic, communicate important information, and promote a sense of trust and confidence in the community's ability to respond to the crisis.
4. Economic and resource stability: The economic and resource stability of a community can also be an important dimension of resilience during the pandemic [62]. Communities with greater economic stability may be better able to support individuals and families who are struggling financially due to the pandemic, while communities with greater resource stability may be better able to provide critical supplies and services to those in need [61]. This can help promote social–psychological wellbeing by reducing stress and providing a sense of security.

Overall, the different dimensions of community resilience are closely related to social–psychological wellbeing during the COVID-19 pandemic. By promoting social connectedness, adaptive capacity, effective leadership and governance, and economic and resource stability, communities can help support individuals and families during this challenging time.

Table 1 The key attributes of community resilience discussed in the literature

Source reference	The key attributes of community resilience						Methodology	Aim
	Ecological	Social	Economic	Institutional	Infrastructure	Health/ Wellness		
Mayunga [41]	✓	✓	✓			✓	No data	Measurement
Foster [17]			✓		✓	✓	Survey	Measurement
Cutter et al. [11]	✓	✓	✓	✓	✓	✓	No data	Measurement
Cutter et al. [10]		✓	✓	✓	✓	✓	U.S. Census/FEMA	Measurement
Links et al. [36]		✓	✓	✓	✓	✓	Public data	Prediction
Ostadtaghizadeh et al. [51]	✓	✓	✓	✓	✓	✓	Literature review	General understanding
Wannous and Velasquez [78]	✓	✓	✓	✓	✓	✓	Survey	Measurement
Cai et al. [6]	✓	✓	✓	✓	✓	✓	Literature review	General understanding
Our paper		✓				✓	Fake and real tweets in Tweeter	Measurement

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 [8, 45]. Coppersmith et al. [8] 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 can provide insights into specific mental disorder and health. Molyneaux et al. [45] examined the relationship between social networking sites and CR using a survey of Internet users.

Li et al. [34] analyzed emotions and psychological states extracted from the datasets of Weibo users using the LIWC [53, 63]. Hou et al. [25] examined risk perception, negative emotions (e.g., sadness, anger, and 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. Vosoughi et al. [75] analyzed true and false rumors in tweets to examine emotions (e.g., surprise, disgust, fear, anger, sadness, anticipation, joy, and trust) in replies using the National Research Council Canada (NRC) [58] and LIWC. Additionally, Naseem et al. [46] analyzed attitudes toward the COVID-19 by focusing on individuals who interact with and share social media on Twitter to ascertain positive and negative sentiments. Reddy et al. [56] examined strategies to detect fake news based solely on the textual characteristics of the news without using any other associated metadata.

However, the works cited above do not incorporate the concept of CR nor explore how to measure social–psychological attributes from both real and fake social media information. Further, no comparison of sentiment analysis under multiple countries has been conducted to investigate different behavioral patterns of dealing with disasters based on unique national characteristics. In this work, we fill this gap.

Social–psychological community resilience

Relative to the works cited above on CR (in Sect. 2.1) and sentiment analysis (Sect. 2.2), our work focuses on social–psychological community resilience (SPCR) for dealing with the COVID-19 in terms of people's social and psychological resilience. We are motivated by *transformative resilience* (TR) [19] in that it is more important to rebuild and reinvent our communities as a more resilient post-disaster state, not simply return to a pre-disaster state. In this sense, fast information diffusion and effective and efficient resource distributions via social networks have been recognized as the key asset to mitigate risks from the disaster and minimize its impact [48]. In particular, Gotham and Campanella [19] identified human and social capitals as the core factors of TR, which can be fundamental driving factors to promote social, economic, and ecological diversity and self-reliance. Therefore, we quantify social–psychological community resilience (SPCR) based on community wellbeing measured by people's mental, and social wellbeing as well as community capital measured by the values and cohesion people communicate with others to build a new post-disaster state of the community via cooperation. To the best of our knowledge, no prior work has quantified social–psychological community resilience based on social media information where both community wellbeing and capital are considered as the key attributes to represent the social and societal resilience as the core attributes of TR.

Data-driven measurement of social–psychological community resilience

In this section, we formally define our proposed SPCR metric comprising community capital (CC) and community wellbeing (CW). We also discuss how we measure SPCR based on lexical and behavioral features captured from tweets using text-mining tools.

Social–psychological community resilience (SPCR) metric

We measure SPCR with respect to the level of community functionality at time t, denoted by $SPCF(t)$, based on people's social and psychological responses to a disaster. $SPCF(t)$ is estimated by considering both community wellbeing ($CW(t)$) and community capital ($CC(t)$) at time t. Hence, SPCR is measured by

$$SPCR = \int_{t=a}^{b} SPCF(t)\,dt = \int_{t=a}^{b} CW(t) \cdot w_{cw} + CC(t) \cdot w_{cc}\,dt, \tag{1}$$

where $[a, b]$ is the time period considered to measure SPCR. In this work, we consider CW and CC equally by setting $w_{cw} = w_{cc}$ with $w_{cw} + w_{cc} = 1$. However, depending on the emphasis of each community's policy in promoting community resilience, CW and CC can be differently weighted. We normalize CW and CC as real numbers ranged in [0, 1] using min–max scaling [22]. Also, we measure SPCR based on a linear function as having been done by existing works in CR (in Sect. 2.1) and sentiment analysis (in Sect. 2.2). Below, we discuss the details of how the two attributes, CW and CC, are measured using NLP tools (Fig. 2).

Community wellbeing (CW)

According to the World Health Organization (WHO) [12, 79], CW is defined based on two dimensions of wellbeing: social wellbeing (SW) and mental wellbeing (MW). The CW is given by

$$CW = SW(t) \cdot w_{sw} + MW(t) \cdot w_{mw}, \tag{2}$$

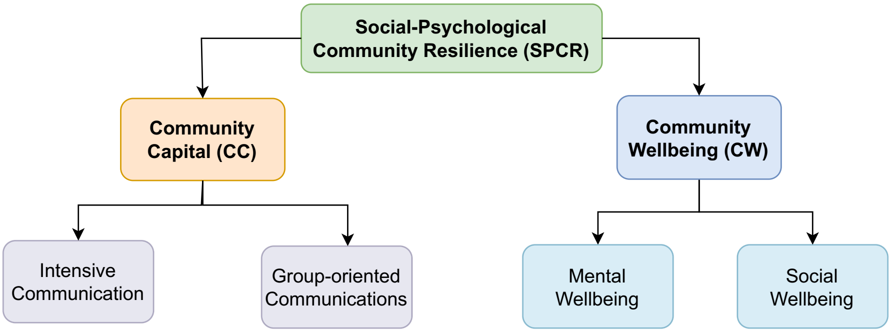


Fig. 2 The social–psychological community resilience (SPCR) consisting of community wellbeing (CW) and community capital (CC) to be measured based on social media information

where the importance of each wellbeing component is considered equally with $w_{mw} = w_{sw}$ where $w_{mw} + w_{sw} = 1$. Again, depending on the emphasis of a given policy in each community, each wellbeing can be considered with a different weight.

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

- Social wellbeing (SW): 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 [54, 74]. Hence, we consider friend, family, and work-related words in the category of LIWC to measure social wellbeing as follows:
  - Friend: Higher social wellbeing can be related to using more social terms in relationships with friends or religions in communication [35, 38].
  - Family: Higher social wellbeing is also related to the frequent use of more familial-related terms, implying a greater sense of family-related wellbeing [64].
  - Work: Higher social wellbeing is sensed when individuals use more work-related terms, such as 'money,' 'achieve,' or 'reward' [14, 21].

  We measure SW using the LIWC categories as follows:ÅÅ

$$\mathrm{SW}(t) = \frac{(\text{LIWC [religion]} + \text{LIWC [family]} + \text{LIWC [money]} + \text{LIWC [friend]})}{\text{LIWC [WC]}} + \frac{(\text{LIWC [reward]} + \text{LIWC [social]} + \text{LIWC [achieve]})}{\text{LIWC [WC]}}, \tag{3}$$

  where, given each country's tweets, LIWC[*social*] refers to the level (output) of social category determined by the LIWC.
- Mental wellbeing (MW): Negative emotional characteristics, such as anxiety, depression, and anger, have been known as the conventional symptoms of

mental illnesses [16, 30, 52]. We measure *anxiety, sadness*, and *anger*, which are in the categories of the LIWC, to represent the overall mental wellbeing of a given community. We measure MW by the LIWC categories as follows:

$$MW(t) = \frac{(\text{LIWC}[anx] + \text{LIWC}[sad] + \text{LIWC}[anger])}{\text{LIWC}[WC]}. \tag{4}$$

Community capital (CC)

We measure CC based on the language patterns representing a community's values and cohesion particularly in terms of promoting community cooperation. CC is captured by the following key attributes:

- Intensive communications (IC): The increased use of complex words and words with more than six letters is known as less efficient for communication, cooperation, and social interaction [42]. To consider this, we measure the opposite degree of 'Words> 6 letter' in the category of the LIWC. We measure IC by

$$IC(t) = \frac{\text{LIWC}[words > 6]}{\text{LIWC}[WC]}. \tag{5}$$

- Group-oriented communications (GC): The frequent use of the first-person pronounce (e.g., 'we,' 'us,' and 'our') indicates group-oriented interaction and cohesion [60]. Assent-related languages (e.g., 'agree,' 'OK,' and 'yes') are known to promote group consensus, interaction, and cooperation in psychological linguistics [59]. Hence, we measure the frequency of words using the 'first-person plural' pronounces and 'assent' in the categories of the LIWC. We measure GC by

$$GC(t) = \frac{\text{LIWC}[\text{first-person plural}] + \text{LIWC}[assent]}{\text{LIWC}[WC]}. \tag{6}$$

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

The selected five countries and their COVID-19 policy

We choose the following five countries to analyze their SPCR to COVID-19: Australia (AUS), Singapore (SG), Republic of Korea (ROK), the United Kingdom (UK), and the United States (US). The reason of choosing these give countries is because each country's unique COVID-19 management policy and national characteristics may have brought a different impact in dealing with COVID-19. Here, we briefly describe COVID-19 policies the five countries have taken as follows:

- AUS: As one of representative Pacific Island countries, AUS has taken the so-called "aggressive strategy" to proactively eliminate the community transmission of the COVID-19 [3]. This aggressive policy was paid off with low infection and death rates.
- ROK: Research also reports that ROK has shown effective COVID-19 management based on strong leadership and collectivism culture to promote cooperation (or called "weness"), rather than individualism culture [27, 32].
- G: Outside of China, SG has the strongest link with Wuhan, with an estimated 3.4 million people traveling between Wuhan and SG annually. Nonetheless, SG did not instantly enact a countrywide lockdown and recommended social distancing instead. SG has one of the lowest rates of COVID-19 infection cases globally. To better respond to pandemics and outbreaks, the government established 900 public health preparation clinics (PHPCs) nationwide [31]. Using Bluetooth technology, TraceTogether and SafeEntry were created in SG to improve contact tracing and quarantine adherence.
- UK: In the beginning of COVID-19, UK tried to take rational responses to COVID-19 based on the scientific investigation. However, due to pre-mature results from the scientific investigation, which predicted a minimum impact, the government policy failed to take proactive actions to protect their people, and accordingly, the government has suffered from banning people's gatherings [26]. In addition, there has been a challenge associated with privacy-encroaching nature of a government policy as the European countries have strongly advocated people's privacy [33].
- US: In US, proper responses to the COVID-19 have been highly challenging as they become main issues by political parties. In addition, unequal health resource distribution was a main factor that can deteriorate the impact of COVID-19 on people's lives [49].

Our work aims to providing useful insights for policy-makers to effectively guide their policy directions to prepare their communities for a post-COVID-19 generation with the aim of reinventing a new, transformative community that is highly resilient to future disasters. To this end, we explain how SPCR can be measured based on both fake and real tweets and analyze why it is differently observed in each country where SPCR can explain the implication of each country's policy and unique national characteristics (e.g., individualism vs. collectivism).

Procedure for measuring SPCR via social media information

Below we describe the procedure to measure SPCR using social media information (e.g., tweets).

Collecting COVID-19-related tweets

We use Twitter datasets to measure SPCR during the COVID-19 in five countries, including AUS, SG, ROK, UK, and US. We investigate 80,000 tweet identifiers

(IDs) under each country during a COVID-19 period from March to November of 2020 and collect approximately 50,000 tweets for each country. The number of tweets in SG is 50,000, which is observed as the minimum among the five countries. For fair comparison, we use 50,000 tweets for all five countries. After removing non-English tweets and performing shuffling, each country ends up with 42,000 tweets. Finally, we make these tweets ordered chronologically from March to November 2020.

Classifying all tweets as real or fake based on top machine learning classifiers

To analyze the SPCR based on both real and fake tweets, we first classify the tweets into real (or true) and fake tweets. We leverage eight well-known machine learning (ML) classifiers and train those eight ML classifiers using the datasets in [2], containing 23,481 fake tweets and 21,417 real news articles. Based on the prediction performance of all eight ML algorithms, as shown in Table 2, we select top three ML algorithms, namely, Passive-Aggressive, Decision Tree, and AdaBoost. As shown in Table 2, these top three ML classifiers can provide 99.5% accuracy. Hence, we do not use additional ML classifiers to further optimize the detection quality of fake news.

Using these top 3 ML algorithms, we predict the truthfulness of each tweet and determine the final prediction for each tweet (true of fake) based on the majority rule of the three ML algorithms (i.e., at least 2 ML classifiers should give a same prediction result).

Identifying CW and CC features using LIWC

Next, we use LIWC as our text-mining tool to extract each country's response to COVID-19, because it can provide a rich volume of diverse social and psychological features and behavioral patterns that can represent CW and CC. Before analyzing tweets using the LIWC, we order all tweets monthly and clean datasets using various NLP tools (i.e, nltk, string, stopwords, RegexpTokenizer,

Table 2 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

Table 3 Attributes of community resilience (CR) and LIWC features to measure the CR

Attribute of CR	Categories in the LIWC
Community wellbeing	
Social wellbeing	Religion, family, money, social, friend, achieve, reward, and word count
Mental wellbeing	Anxiety, sadness, anger, and word count
Community capital	
Intensive communications	Words> 6 letters and word count
Group-oriented communications	First-person plural, assent, and word count

Table 4 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	$\frac{p_1 \times x^2 + (p_2 \times x) + p_3)}{(x^3 + q_1 \times x^2 + q_2 \times x + q_3)}$
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	$1 - \frac{(RSS/(n-N^{var}-1))}{(TSS/(n-1)))}$

regexp, WordNetLemmatizer, and PorterStemmer) for each country's fake and real tweets. Specifically, we first remove HTML, punctuation, stop words, and word stammering. Then, we extract all LIWC features considered to assess the measurement of SPCR.

Measuring SPCR based on the extent of exhibiting the considered LIWC features

Finally, we measure SPCR based on all the LIWC features considered in Table 3. To effectively capture the dominant trends of SPCR in each country using the tweeter datasets, we use fitting curves to extract the trends of SPCR. To optimize the accuracy of the fitting curves, we examine multiple fitting functions and obtain 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_A^2 [37]. For our paper to be self-contained, we summarize how each fitting function is presented and how each goodness metric is calculated in Table 4.

Table 5 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

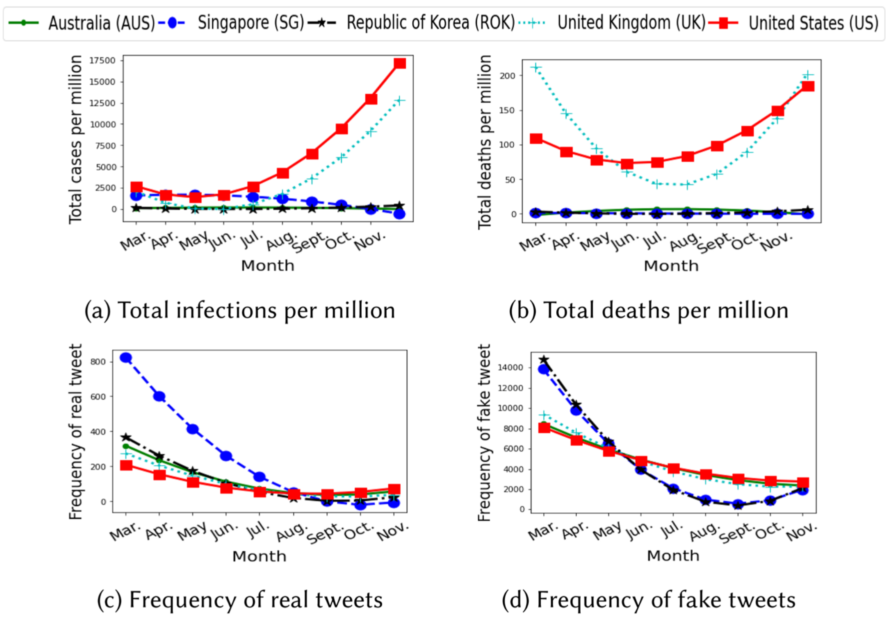
To provide the example goodness metrics of various fitting curves shown in Table 4, we generate goodness values using the dataset on the CC of fake tweets in Table 5. For Exponential, Gaussian, and Rational functions, there is no optimal fitting curve. The polynomial function had the highest level in R^2 and R_A^2 while showing the lowest level in R and RSS. Therefore, we choose the polynomial fitting function to analyze the trends of the measured SPCR along with the measured CW and CC.

Experimental results and analysis

In this section, we first discuss the real/fake tweets data from five countries (AUS, SG, ROK, UK, and US) used for experimental evaluation. Then we explain how we measure community wellbeing, community capital, and consequently SPCR from tweets data. Finally, we analyze the trends obtained and provide physical interpretations behind the observed trends.

Tweets datasets

Figure 3 displays the total numbers of the COVID-19 infection cases and deaths per million population and the frequencies of fake and real tweets in five countries (i.e., AUS, SG, ROK, UK, and US) during the period of March-November 2020. All tweets were first classified into real and fake tweets following the classification procedure discussed in Sect. 3.3. It is noticeable that during the period of March–November 2020, US and UK had experienced substantially higher infection and death cases than the other three countries. In addition, SG had a decreasing trend in both infection and death cases over time. Although the number of death cases dropped a little during the summer (e.g., June–August 2020), it increased again going toward the winter season. Unlike the resurgence of infection and death cases in the UK and US, the amount of real and fake news kept decreasing overall with slight resurgence during October/November 2020. One interesting observation is that SG had a substantially larger amount of real tweets than other countries (see Fig. 3). In addition, SG and ROK both exhibited a substantially decreasing trend



(a) Total infections per million (b) Total deaths per million

(c) Frequency of real tweets (d) Frequency of fake tweets

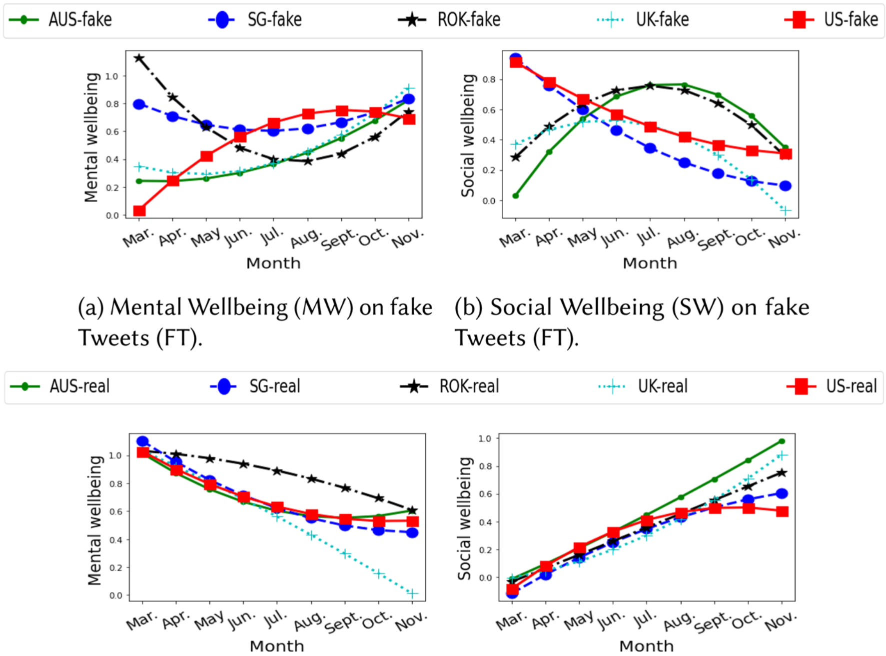
Fig. 3 Total numbers of infections per million, total numbers of deaths per million, the frequency of real tweets, and the frequency of fake tweets for the five countries during March–November 2020

of fake tweets, even though a larger amount of fake tweets were generated in the beginning of COVID-19 (e.g., March–April 2020) compared with the other three countries. AUS also had a similar trend in generating real and fake tweets. However, AUS exhibited a vastly different trend in the COVID-19 infection and death cases from the US and UK. Since AUS is positioned uniquely with a low population density compared to US and UK, it may put AUS in a more advantageous position to deal with COVID-19.

Measures of community wellbeing

In this section, we present and analyze the trend of *community wellbeing* (CW) which is the first attribute of SPCR. Recall that CW comprises mental wellbeing (MW) and social wellbeing (SW), and the procedure for measuring CW was discussed in Sect. 3.1 and Sect. 3.3.

Figure 4 shows the mental wellbeing and social wellbeing of five countries during the same period of March–November 2020. The following general trends are observed: (1) MW measured on fake tweets (Fig. 4a) fluctuates over time with SG experiencing a low peak and US experiencing a high peak in the middle; (2) SW measured on fake tweets (Fig. 4b) also fluctuates over time with AUS, ROK, and UK experiencing a high peak in the middle); (3) MW measured on real tweets (Fig. 4c) steadily decreases over time; (4) SW measured by real tweets (Fig. 4d) steadily increases over time. These trends point to the detrimental effect of false



(a) Mental Wellbeing (MW) on fake Tweets (FT).

(b) Social Wellbeing (SW) on fake Tweets (FT).

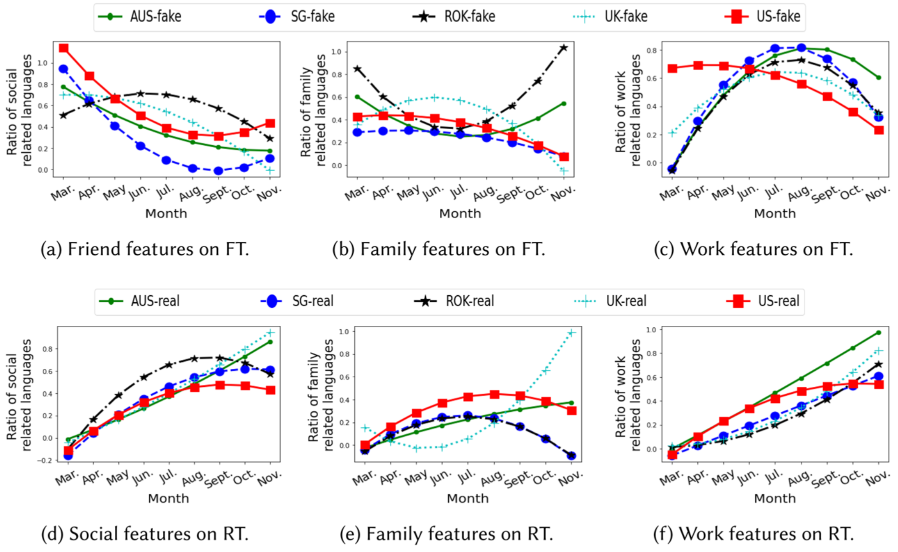
(c) Mental Wellbeing (MW) on real Tweets (RT).

(d) Social Wellbeing (SW) on real Tweets (RT).

Fig. 4 Community wellbeing measured by mental wellbeing (MW) and social wellbeing (SW) using real tweets (RT) and fake tweets (FT) in five countries during the period of March–November 2020

tweets causing fluctuating patterns of MW or SW which may altogether contribute to instability of community wellbeing (CW) over time. In particular, we observe that among the five countries studied, ROK appears to exhibit the most unstable MW and SW on false tweets, suggesting that false tweets in quantity may change rapidly in ROK during the COVID-19 period of March–November 2020. This matches Fig. 3d which shows the month-by-month frequency of fake tweets in five countries during March–November 2020. On the contrary, real tweets are able to provide a steady pattern for both MW and SW which altogether offer a steady pattern for CW. This is observed for all five countries.

Below, we investigate the effect of the three dimensions of social wellbeing (SW), namely, friend, family, and work (as discussed in Sect. 3.1), and analyze the underlying implications. Figure 5 shows the effect of friend, family, and work-related features on SW using real and fake tweets in five countries during March–November 2020. We observe that (1) in friend-related features, overall SW decreases on fake tweets and increases on real tweets over time, with SG being the country with the lowest SW on fake tweets while maintaining a modest level of SW on real tweets when compared with other countries; (2) in family-related features, the SW trend is very unique for each country on real and fake tweets and there is no clear winner



(a) Friend features on FT. (b) Family features on FT. (c) Work features on FT.

(d) Social features on RT. (e) Family features on RT. (f) Work features on RT.

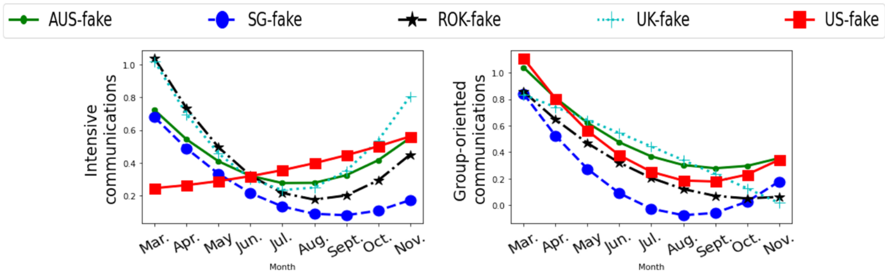
Fig. 5 Social wellbeing measured by friend, family, and work features in LIWC using real tweets (RT) and fake tweets (FT) in five countries during March–November 2020

among the five countries; and (3) in work-related features, all countries reach a high peak over time and then go down on fake tweets and steadily increase SW over time on real tweets. In particular, We observe that in AUS for work-related features, SW can reach a very high level over time on real tweets and its increasing rate is impressive. This can explain AUS's fast recovery from COVID-19 compared to the other countries. Overall, we observe that social wellbeing increases on real tweets and decreases on fake tweets. This concludes that fake tweets have detrimental effects on SW and consequently on CW.

Measures of community capital

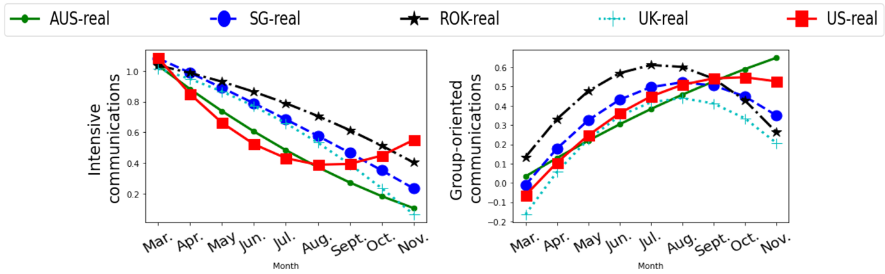
In this section, we present and analyze the trend of *community capital* (CC) which is the second attribute we propose to measure SPCR. Recall that CC comprises intensive communications (IC) and group-oriented communications (GC) and the procedure for measuring CC was discussed in Sect. 3.1 and Sect. 3.3.

Figure 6 shows IC and GC obtained from tweets data in five countries during the same period as before. We observe that (1) on fake tweets (see Fig. 6a and Fig. 6b), both IC and GC decrease and then increase over time with US being the only exception with monotonically increasing IC over time; (2) on real tweets (see Fig. 6c and Fig. 6d), IC monotonically decreases over time with US being the exception exhibiting a down-and-up trend over time; GC is up-and-down over time with AUS being the only exception with monotonically increasing GC; (3) all countries exhibit roughly the same trend in IC with US standing out as the only exception; (4) all countries exhibit roughly the same trend in GC with UK being the only exception



(a) Intensive Communications (IC) on FT.

(b) Group-oriented Communications (GC) on FT.



(c) Intensive Communications (IC) on RT.

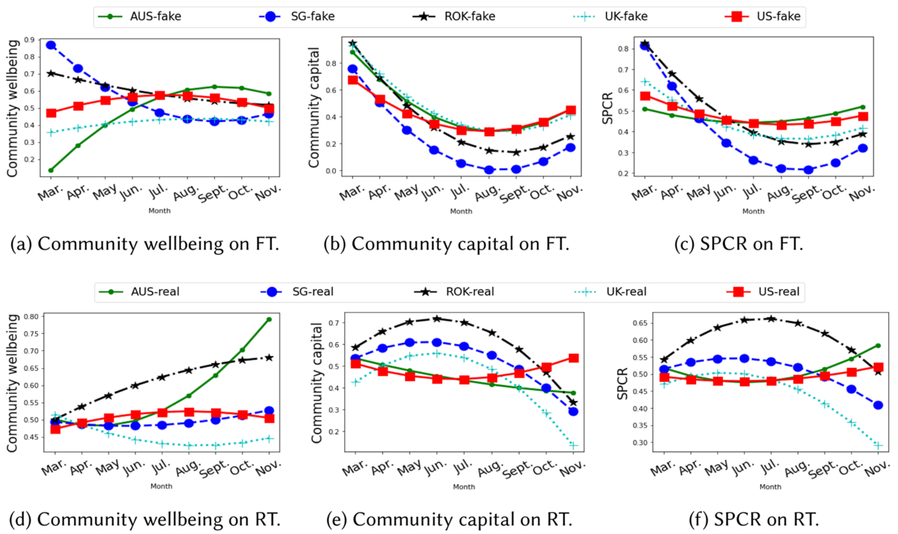
(d) Group-oriented Communications (GC) on RT.

Fig. 6 Community capital measured by intensive and group-oriented communications using real tweets (RT) and fake tweets (FT) in five countries during March–November 2020

on fake tweets and AUS being the only exception on real tweets. The high level of IC and GC on fake tweets by US and UK is especially alarming, because it reflects a very high level of exposure and discussion among people issuing or following fake tweets on the social network platform, which helps spread misinformation (e.g., vaccination is harmful) and deters a fast COVID-19 recovery. This may partially explain why there is a slow recovery of COVID-19 in US and UK. On the other hand, the high level of IC and GC on real tweets by ROK is impressive as it helps spread useful information to fight or cope with COVID-19 and could partially explain why there was a fast recovery in ROK during the COVID-19 period of March–November 2020.

Measures of social–psychological community resilience

In this section, we present and analyze the trend of *social–psychological community resilience* (SPCR). Recall that SPCR comprises community wellbeing (CW) and community capital (CC) whose trends were analyzed in Sect. 4.2 and Sect. 4.3, respectively. The procedure for measuring SPCR was discussed in Sect. 3.3.



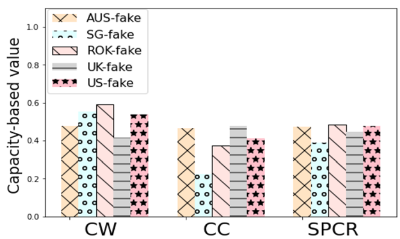
(a) Community wellbeing on FT. (b) Community capital on FT. (c) SPCR on FT.

(d) Community wellbeing on RT. (e) Community capital on RT. (f) SPCR on RT.

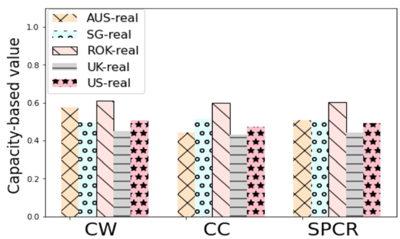
Fig. 7 Community wellbeing (CW), community capital (CC), and social–psychological community resilience (SPCR) measured based on COVID-19 related real tweets (RT) and fake tweets (FT) for the five countries during March–November 2020

Figure 7 shows SPCR on fake and real tweets in five countries over the same period of March–November 2020. For comparison, we also show CW and CC alongside (on the left of the figure) as SPCR comprises CW and CC by Eq. 1. We see that SPCR is remarkably similar to CC over time. On fake tweets, all countries exhibit a down-and-up trend over time with US and AUS having the highest level of SPCR. On real tweets, US and AUS again exhibit a mild down-and-up trend over time and all other countries exhibit a up-and-down trend over time with ROK having the highest level and UK having the lowest level of SPCR among all. These trends can be understood as the influence of each country's policy to manage COVID-19, such as AUS's aggressive lockdown strategy to maintain zero cases, SG's strong responses to maintain people's wellbeing, ROK's strong government leadership and Korean people's willingness to follow vaccination/masking mandates, UK's movement to advocate privacy and to live with virus, and US' effort to distribute health resources and political divides with regards to vaccination/masking mandates which affect people in different areas of the country. The ROK's government's proactive and aggressive approach to testing and contact tracing helped to identify and isolate infected individuals quickly, which helped to prevent the spread of the virus within communities. This allowed people to feel more confident and safe in their daily lives, which in turn improved their wellbeing. Plus, the ROK's government's communication strategy was clear and consistent, which helped to build trust and confidence among the public. This trust and confidence were important for ensuring that people followed public health guidelines and restrictions, which helped to keep infection rates low and prevent the healthcare system from becoming overwhelmed. The government provided financial support to businesses and individuals affected by the pandemic, which helped to reduce economic insecurity and protect people's livelihoods. This support helped to maintain social capital and prevent a sense of disconnection and disengagement from society. Plus, the AUS's lockdown measures may have helped reduce the transmission of COVID-19 and prevented widespread illness and death. This outcome could have had a positive effect on community wellbeing. Moreover, the government's financial assistance packages and support programs may have helped bolster community capital during the lockdown period.

In the resilience literature, there are two types of resilience measurements: output-oriented and capacity-based [82]. Figure 7 above is based on output-oriented measurements. While output-oriented measurements yield accurate information about the trend and dynamic change of functionality, capacity-based measurements show the time-weighted overall functionality. Hence, we also perform capacity-based measurement of SPCR for comparison purposes. Figure 8 shows capacity-based CW, CC, and SPCR on fake and real tweets in five countries. We observe that SPCR on real tweets is up to 80% higher than SPCR on fake tweets with ROK, AUS, and SG having a higher level of SPCR than US and UK. On fake tweets, ROK, US, and AUS have a higher level of SPCR than UK and SG. The difference between SPCR measured from real tweets and SPCR measured from fake tweets demonstrates social media can significantly affect SPCR where the difference is 0.03, 0.12, 0.12, 0.00, and 0.02 for AUS, SG, ROK, UK, and US, respectively. We also observe that SG and ROK are highly affected by fake tweets. That is, SG and ROK perceive a disaster more pessimistically, which may lead to more precautions behaviors to handle the disaster and can naturally result in less detrimental impacts than other countries which may perceive the disaster too optimistically. Also, ROK has the highest level of SPCR on real tweets which reflect reality, which can partially explain why ROK is resilient to COVID-19 during March–November 2020. ROK's response to COVID-19 has been viewed as more effective compared to other countries. South Korea implemented a proactive and aggressive approach to testing and contact tracing, which helped to contain the spread of the virus. The government also implemented strict quarantine measures for people entering the country, as well as social distancing measures and mandatory mask-wearing. Plus, AUS's response to COVID-19 has



(a) Capacity-based CW, CC, and SPCR on fake tweets.



(b) Capacity-based CW, CC, and SPCR on real tweets.

Fig. 8 The capacity-based values of reliance-related metrics: community wellbeing (CW), community capital (CC), and social–psychological community resilience (SPCR) also been viewed as effective as South Korea's response. Australia has implemented strict border controls and quarantine measures, implemented widespread testing and contact tracing, and enacted lockdowns and social distancing measures when necessary. The Australian government has also provided financial support to businesses and individuals affected by the pandemic. SG's response to COVID-19 has also been effective. Singapore implemented a comprehensive strategy that included widespread testing and contact tracing, quarantine measures, mandatory mask-wearing, and social distancing measures. The government also launched a comprehensive public health communication campaign to educate and inform the public about the risks and best practices for preventing the spread of the virus. The USA' response to the pandemic has been criticized for being fragmented and inconsistent, with a lack of cohesive national strategy. While some states implemented strict measures early on, others did not, and there was significant resistance to mask-wearing and social distancing in some areas. The federal government's response was also criticized for being slow and inadequate. The UK's response to COVID-19 was slower and less effective compared to other countries. The UK initially adopted a "herd immunity" strategy, which was later abandoned in favor of a national lockdown. There were also delays in implementing testing and contact tracing, and the government's messaging was at times unclear and inconsistent. It is worth noting that there are many factors that can influence a country's response to a pandemic, including demographics, geography, political climate, and existing healthcare infrastructure.

Correlation of the SPCR between fake and real tweets

To deeply understand the correlation of resilience measures from fake tweets and real tweets, we calculate statistical correlation coefficients based on Pearson's and Spearman's correlation coefficients. These two correlation coefficients demonstrate the linear and monotonic relationships between two variables, x, and y [9]. We choose Pearson's correlation coefficient to investigate if there is a linear statistical relationship or association between a resilience metric measured from real tweets (x) vs. the same resilience metric measured from fake Tweets (y). The Pearson correlation coefficient uses an assumption that both x and y are normally distributed. When this assumption does not hold, we rely on a non-parametric approach, such as Spearman's correlation, which does not make any assumption about distribution. Table 6 shows Pearson's and Spearman's correlation coefficients of SPCR and its associated resilience metrics on fake and real tweets in five countries. This table lists the maximum-likelihood values of correlation coefficients obtained by a fitting function with non-linear least-squares regression. In general, the two correlation coefficients are highly similar, indicating high consistency in correlation (i.e., both positive and negative correlations) obtained by parametric and non-parametric analysis, except the two cases: (1) SG's 'mental wellbeing'; and (2) 'Work' as a determinant of social wellbeing in ROK. However, the correlation coefficients are low with opposite signs.

Table 6 shows that for SG, ROK, and UK, the correlations between CW on fake tweets and CW on real tweets are negative. For the submetrics, MW and SW, under

Table 6 Pearson and spearman correlation coefficients of SPCR and its associated attributes between fake and real tweets under the five countries after removing outliers

SPCR att.	Country	AUS		SG		ROK		UK		US		All	
	Coeff	P	S	P	S	P	S	P	S	P	S	P	S
CW	MW	− 0.67	− 0.77	0.11	− 0.17	0.37	0.43	− 0.91	− 0.88	− 0.99	− 0.92	− 0.61	− 0.63
	SW	0.41	0.43	− 1.00	− 1.00	0.01	0.17	− 0.86	− 0.63	− 0.98	− 0.95	− 0.87	− 0.95
	Total	0.61	0.77	− 0.36	− 0.50	− 1.00	− 1.00	− 1.00	− 0.95	0.90	0.93	− 0.40	− 0.43
CC	IC	0.48	0.17	0.82	0.78	0.61	0.63	0.13	0.17	− 0.66	− 0.63	0.70	0.43
	GC	− 0.91	− 0.88	− 1.00	− 1.00	− 0.58	− 0.20	− 0.62	− 0.43	− 0.98	− 0.88	− 0.97	− 0.95
	Total	0.84	0.63	0.21	0.10	0.17	0.35	0.15	0.35	0.60	0.75	− 0.18	− 0.20
SPCR		0.85	0.93	0.28	0.35	− 0.27	− 0.07	0.36	0.55	− 0.02	− 0.10	− 0.14	− 0.20

Note: *P* Pearson correlation coefficient, *S* Spearman correlation coefficient, *SPCR* Social–Psychological Community Resilience, *CW* Community Resilience, *MW* Mental Wellbeing, *SW* Social Wellbeing, *CC* Community Capital, *IC* Intensive Communication, *GC* Group-oriented Communications

CW, we observe that (1) 70% of the cases shows a negative correlation between MW on fake tweets and MW on real tweets. However, both correlations show positive for ROK; and (2) 60% of the cases shows a negative correlation between SW on fake tweets and MW on real tweets. Similarly, both correlations show positive for AUS and ROK.

We also observe that the correlations under 'Total CC' (i.e., CC itself) and 'All' (i.e., all countries) show negative (i.e., − 0.18 and − 0.20), while the correlation under 'Total CC' and each country (e.g., AUS, SG, ROK, UK, or US) is positive. For the two metrics (IC and GC) under CC, we observe that (1) except for US, the correlation between IC on fake tweets and IC on real tweets is positive; and (2) in all countries, there is a negative correlation between GC on fake tweets and GC on real tweets (i.e., − 0.97 and − 0.95). Note that real tweets can be used as a true representative of the SPCR as they reflect reality, as opposed to fake tweets showing irrational perception toward the reality. We can consider a higher level of positive correlation as a positive sign compared to a negative correlation because we want people to think close to reality. Different correlation values for different countries therefore can be considered as due to distinct national (i.e., community) policies, behaviors and characteristics. According to our findings, ROK and AUS exhibit the best SPCR to handle COVID-19 among other countries in terms of both real and fake tweets. In addition, while the correlations of SPCR on fake tweets and SPCR on real tweets are negative for ROK and US (i.e., − 0.27 and − 0.07 for ROK and − 0.02 and − 0.10 for US), all other countries show positive correlations. In addition, the correlation in SPCR for all countries (i.e., under 'All' representing the aggregate of all countries) is negative (i.e., − 0.14 and − 0.20). In other words, as the level of SPCR on fake tweets increases, the level of SPCR on real tweets decreases. This implies that perception through fake tweets differs from that through real tweets about COVID-19. As real tweets reflecting truth can better represent reality, fake tweets can introduce false perception toward COVID-19 and thus introduce undesirable behaviors to deter a fast recovery from COVID-19.

Conclusion

This section summarizes the key contributions made in this work and answers the research questions raised in Sect. 1.2. In addition, we suggest future research directions.

Summary of the key contributions

In this work, we proposed a novel social–psychological community resilience (SPCR) metric as an indicator of community resilience toward a disaster, i.e., COVID-19, using social media information. To measure SPCR, we considered two key attributes: community wellbeing (CW) and community capital (CC). We measured CW based on social and mental wellbeing while measuring CC based on intensive communication and group-oriented communication patterns in people's language use in tweets. Our work is the first that proposed a novel SPCR metric using these two attributes captured based on social media information. This proposed metric framework is generic and applicable to measure SPCR for other disasters.

We used top three machine learning (ML) algorithms among eight ML algorithms being evaluated, i.e., Passive-Aggressive Classifier, Decision Tree Classifier and AdaBoost Classifier. The three ML algorithms showed at least 95% accuracy to classify 210,000 tweets during a COVID-19 period of March–November 2020 into fake and real tweets based on the majority rule as our experimental tweets dataset. We investigated the trends observed in the measured SPCR in the five selected countries, including Australia (AUS), Singapore (SG), Republic of Korea (ROK or South Korea), the United Kingdom (UK), and the United States (US), and provided implications and insights to relate SPCR to COVID-19 recovery in these countries. We also examined the linear and monotonic correlations between SPCR (and its attributes) obtained from fake tweets and SPCR (and its attributes) obtained from real tweets to understand their similarities based on Pearson and Spearman's correlation coefficients.

Answers for the research questions

RQ1. *What are the main trends observed in SPCR and our proposed key attributes for measuring SPCR [i.e., community wellbeing (CW) and community capital (CC)] and what are the physical implications of the trends observed for five different countries (i.e., AUS, SG, ROK, UK, and US) on COVID-19?*

Answer. Figure 8 summarizes the main trends of CW, CC, and SPCR, comprising equal-weighted CW and CC in this study, in the five countries. In our experiments, we observe their overall extents in the following order: ROK≥SG≥US≥AUS≥UK for CW, AUS≥UK≥US≥ROK≥SG for CC, and ROK≥US≥AUS≥UK≥SG for SPCR. We notice that on fake tweets, the ranking order in CW and CC is not necessarily in line with the ranking order in SPCR. The ranking order of countries on real tweets on these metrics is: ROK≥AUS≥SG≥US≥UK for CW, ROK≥SG≥AUS≥US≥UK for CC, and ROK≥AUS≥SG≥US≥UK for SPCR. We notice that on real tweets the ranking order in CW and CC is generally in line with the ranking order in SPCR. This implies that people in the community of real tweets which reflects a more common or consistent view toward CW and CC resilience metrics. In particular, ROK shows the highest CW, CC, and the resulting SPCR on real tweets matches well with the fact that ROK is resilient to COVID-19 during March–November 2020.

RQ2. *What are the key differences and correlations between SPCR measured on fake tweets and SPCR measured on real tweets?*

Answer. Our results indicate that SPCR on real tweets is up to 80% higher than SPCR on fake tweets. This gives an insight that the community consisting of people who issue/follow real tweets has a higher SPCR than the community consisting of people who issue/follow fake tweets. Our results also show that there is a negative correlation between SPCR on fake tweets and SPCR on real tweets across all countries (i.e., aggregating all tweets without country distinction). When the outcomes of both fake and real tweets are assumed to be normally distributed in Pearson correlation coefficient, their correlation is −0.14. On the other hand, when no prior distributional assumptions are made (i.e., Spearman correlation coefficient), their correlation coefficient is −0.20. Both correlation methods, therefore, confirm the correlation as negative. This implies that the SPCR measured by fake and real news shows the opposite correlation and fake news can easily mislead people's perception toward COVID-19 and may influence the way they handle COVID-19 accordingly.

RQ3. *What are the key differences and correlations of the measured SPCR in five different countries when SPCR is measured on fake or real tweets?*

Answer. Table 6 shows that AUS, SG, and UK exhibit a positive correlation between SPCR on fake tweets and SPCR on real tweets, with the Spearman correlation coefficients being 0.93, 0.35, and 0.55, respectively. The other two countries, i.e., ROK and US, exhibit a negative correlation, with the Spearman correlation coefficients being −0.07 and −0.10, respectively. When we aggregate all tweets across the country boundary as input, there is a negative correlation between SPCR on fake tweets and SPCR on real tweets with the Spearman correlation coefficient being −0.20. Based on these data, we can draw the following conclusions: (1) showing high SPCR on real tweets cannot be an indicator to draw a certain (i.e., positive or negative) correlation. For example, AUS shows high SPCR on real tweets but the positive correlation between SPCR values measured by fake and real tweets. For ROK with high SPCR on real tweets, there was a negative correlation between SPCR values on fake and real tweets; (2) however, overall, we found that there is a negative correlation between SPCR values on fake and real tweets. Thus, we should be very careful in analyzing the correlation between these two by considering each country's unique cultural and national characteristics, which is left for our future work. Therefore, although we cannot say that all countries have a negative correlation between these two measures (i.e., SPCR on fake and real tweets), it is still insightful to observe the overall trends show there exists a negative correlation between SPCR values on fake and real tweets. We believe that this conclusion is still convincing to motivate investigating how to eradicate or mitigate fake news about a disaster to build a sustainable social system.

Future research directions

We suggest the following future research directions.

First, as we observed in our experimental results, we should be extremely careful to analyze social media information based on a unified tool without considering each country's unique cultural and national characteristics. Based on these unique traits of each country, how to perceive a disaster is different and accordingly how to handle it based on their unique historical experiences will be different. In-depth understanding, modeling, and simulating of unique cultural and national characteristics should be the first step to tackle this community resilience problem.

Second, although we propose to measure community resilience via social media information (e.g., tweets) in this work, we are still in the first phase of this road, namely, enhancing community resilience. The prediction models for community resilience are not thoroughly investigated in the literature. As a result, more sophisticated models are required to anticipate the response of distinct communities to various events and epidemics. In particular, it calls for developing a multi-agent model that takes fake news spread into account. To validate the model, the approach described in this work needs to be further extended. The next step on this route is to use machine and deep learning techniques to predict output-oriented community resilience.

Third, once we evaluate how communities respond to various disasters, we can consider designing tools and policies to increase community resilience to epidemics, such as COVID-19 or other disasters. To increase community resilience, one can develop mathematical optimization models, such as mathematical programming with equilibrium constraints, equilibria programming with equilibrium constraints, deep reinforcement learning, and heuristic algorithms.

Finally, based on social characteristics of a community and the perspectives of its stakeholders, one can choose appropriate engagement strategies, such as collaborative adaptive management and joint fact-finding, to determine proper policies to enhance community resilience.

Acknowledgment ACM acknowledges that this contribution was authored or co-authored by an employee, contractor, or affiliate of the UnitedStates government. As such, the United States government retains a nonexclusive, royalty-free right to publish or reproducethis article, or to allow others to do so, for government purposes only.

Data availability The data are available at https://github.com/Jab-V/Community-Resilience-to-COVID-19-Using-Social-Media.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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