Evolution of COVID-19 tweets about Southeast Asian Countries: topic modelling and sentiment analyses

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Abstract
Despite the global scale of this pandemic, comparison and contrast of topics, sentiment and emotions of tweets among countries are limited. Further, most previous studies covered a short timeframe due to the recency of the event and the large volume of tweets. The purposes of this research were to (1) identify the multiplicity of public discourse about countries during the COVID-19 pandemic and how they evolved, (2) compare and contrast sentiment levels and (3) compare emotions about countries over time. The research scope covered 115,553 tweets that mentioned ten countries in Southeast Asia (SEA) from 22 January 2020 to 31 July 2021. This research presents the infoveillance methods—using a topic modelling algorithm (LDA), VADER and NRC sentiment analyses—that elucidated the evolution and the emergence of public narratives and sentiment affecting country brands during the pandemic. Results also shed light on the role of word-of-mouth (WOM) communications in the place branding process.

Keywords COVID-19 pandemic · Twitter · Topic modelling · Sentiment analysis · Southeast Asia · Place branding

Introduction

Due to the severe impacts on health, societies and economies worldwide, copious research has studied the use of Twitter during the COVID-19 pandemic to better understand the tenets of public discourse. Notwithstanding their positive contributions, these studies have left two research gaps. First, previous authors determined that conversations on Twitter about public health crises such as H1N1 (Chew and Eysenbach 2010) and Ebola (Roy et al. 2020) changed over time, while research investigating how public discourse, sentiment and emotions about COVID-19 evolved had limited timeframes, mostly ranging between 2 and 4 months (e.g. Basiri et al. 2021; Mansoor et al. 2020; Zhou et al. 2021). A temporal dimension of online discussions is crucial for a comprehensive understanding of the situation (Lyu and Luli 2021).

Second, due to the scale of the crisis, public discourse about each country is unlikely to be homogeneous. Recent research found that local events influenced the sentiment of tweets from different countries (Basiri et al. 2021; Mansoor et al. 2020). However, the contents of COVID-19 tweets about countries have not been thoroughly analysed. This research gap is important because public discourse and communications about a country on social media—the so-called electronic word-of-mouth (WOM)—shape the meaning and “brand” of that country (Andén et al. 2014) which, in turn, affects the country’s image and reputation (Avraham 2018). Research found that public health communications about COVID-19 varied across time and space (Slavik et al. 2021). However, little research has been done to shed light on such a variability.

The evolution of multiple COVID-19 public discourse about countries presented the research lacuna that this research aimed to fill. Therefore, this research had three primary objectives to (1) identify the multiplicity of public discourse about countries during the COVID-19 pandemic and how it evolved, (2) compare the changes of sentiment in tweets and (3) compare emotions about countries over time. The scope of this research covered countries in Southeast

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Asia (SEA) that belonged to the Association of Southeast Asian Nations (ASEAN). The timeframe of our analysis extended for over 18 months after the first case was detected in the region. This research analysed 115,553 tweets about the pandemic that mentioned the 10 SEA countries between January 2020 and July 2021. An unsupervised machine learning topic modelling algorithm (latent Dirichlet allocation—LDA) and sentiment analyses (VADER and NRC) were used to categorise tweets and assess their sentiment/emotions.

Zhao et al. (2018) posited that it is essential for responsible agencies to adopt a public-centric perspective on crisis communications. The country’s ability to manage its “brand” depends on how it responded to the crisis (Lee and Kim 2021). The widespread global adoption of digital and mobile technology, which has become a powerful tool for listening to the international public (Di Martino 2020), made the understanding of information on social media a critical issue during the COVID-19 pandemic. The findings of this research will help us to understand the evolving multiple public discourse, sentiment and emotions concerning these 10 countries during the pandemic. The method used in this research can also help elucidate the role of WOM communications in the place branding process.

COVID-19 tweets about countries

Tweets during the COVID-19 pandemic

As an important source of information during the COVID-19 pandemic, Twitter offers the potential for surveillance of public perceptions and emotions. Surveillance methods that include mining, aggregating and analysing digital data in real-time are also referred to as “Infoveillance” (Chew and Eysenbach 2010). One of the infoveillance methods that has gained prominence during the pandemic is topic identification (modelling) of tweets. LDA, a prominent topic modelling algorithm, has replaced traditional content analysis as the primary technique used by researchers to identify topics (Table 1). Many studies used LDA to identify topics of pandemic-related tweets such as the reporting of news, the origin of COVID-19, global economic and social impacts, government actions and responses (e.g. Boon-Itt and Skunkan 2020; Kwan and Lim 2020; Medford et al. 2020; Mutanga and Abayomi 2020; Zheng et al. 2020). Being able to analyse tweets and categorise them assists responsible agencies and governments to better understand public awareness, attitudes and reactions to anticipate prevalent narratives that are likely to occur (Olteanu et al. 2015; Wicke and Bolognesi 2020).

Other researchers studied public sentiment from tweets using tools such as Valence Aware Dictionary and sEntiment Reasoner (VADER) and NRC Emotion Lexicon (Table 1). Studies found that the general sentiment towards COVID-19 at the beginning of the pandemic was negative (Boon-Itt and Skunkan 2020). However, some authors detected gradual changes from negative to positive as public discourse shifted from panic buying, shortages, lockdown, violence and the devastating impacts to more positive topics such as financial support, prevention measures, telecommuting, e-commerce and treatments (Chandrasekaran et al. 2020; Kwan and Lim 2020). Other studies used sentiment analyses to detect changes in different emotions such as fear, anger, joy and surprise. Lwin et al. (2020) found a shift from fear to

Table 1 Selected studies of COVID-19 tweets

| Author                        | No. of tweets | Period          | Context                        | Analysis             |
|-------------------------------|---------------|-----------------|--------------------------------|----------------------|
| Abd-Alrazaq et al. (2020)     | 167,073       | Feb 20–Mar 20   | General                        | LDA, TextBlob        |
| Basiri et al. (2021)          | 1,056,049     | Jan 20–Apr 20   | US, China, Iran, Italy, Spain, Australia, England, Canada | Deep Learning |
| Boon-Itt and Skunkan (2020)   | 107,990       | Dec 19–Mar 20   | General                        | LDA, NRC             |
| Chandrasekaran et al. (2020)  | 13,937,906    | Jan 20–May 20   | General                        | LDA, VADER           |
| Kwan and Lim (2020)           | 896,031       | Mar 20–Jun 20   | General (Singapore & UK)       | LDA, NRC & AFINN     |
| Lwin et al. (2020)            | 20,325,929    | Jan 20–Apr 20   | General                        | CrystalFeel          |
| Lyu and Luli (2021)           | 290,764       | Mar 20–Aug 20   | CDC                            | LDA                  |
| Lyu et al. (2021)             | 1,499,421     | Mar 20–Jan 21   | Vaccines                       | LDA, NRC             |
| Mansoor et al. (2020)         | 165,116       | Jan 20–Jun 20   | General (US, Brazil & India)    | VADER, NRC           |
| Medford et al. (2020)         | 126,049       | Jan 20          | General                        | LDA, Ekman           |
| Mutanga and Abayomi (2020)    | 68,000        | Mar 20–Apr 20   | South Africa                   | LDA                  |
| Valdez et al. (2020)          | 86,581,257    | Jan 20–Apr 20   | General                        | LDA, VADER           |
| Xue et al. (2020)             | 4,196,020     | Mar 20–Apr 20   | General                        | LDA, NRC             |
| Zheng et al. (2020)           | 940,837       | Mar 20          | General                        | LDA                  |
| Zhou et al. (2021)            | 94,707,264    | Jan 20–May 20   | General                        | VADER                |
anger at the beginning of the pandemic, while sadness from personal loss and joy from gratitude also emerged. Despite these limited findings, a clear inference from various studies is that global online discourse, sentiment and emotions evolved swiftly during the course of the pandemic.

Lyu and Luli (2021) posited that temporal variation and formation of topics are crucial for understanding public discourse about the pandemic. Observations and analyses of such changes can offer a cost-effective and timely method to assess public perceptions (Chandrasekaran et al. 2020). Some studies investigated changes in the characteristics of COVID-19 tweets over time (Basiri et al. 2021; Mansoor et al. 2020; Valdez, Ten Thij, Bathina et al. 2020). However, most covered only a short timeframe, typically between 2 and 4 months, due to the recency of the event and the large volume of tweets. Lyu et al. (2021) investigated a period of 11 months (March 2020–January 2021); however, they only focussed on discussions about vaccines. This research lacuna calls for an in-depth investigation of the evolution of topics, sentiment and emotions over a longer timeframe.

Another contextual gap from the existing literature is the relationship between COVID-19 tweets and countries. Most studies in Table 1 addressed general tweets about COVID-19 without any specific context. Some focused on contexts such as the Centers for Disease Control and Prevention (CDC) (Lyu and Luli 2021) and vaccines (Lyu et al. 2021). Despite the diverse impacts on countries worldwide, comparison and contrast of topics, sentiment and emotions of tweets among multiple countries are limited. Some researchers utilised the geotagging feature of Twitter and explored the correlation between tweets and new COVID-19 cases (Lopez et al. 2020), while others shed light on the impacts of local events relating to the sentiment of tweets from several countries (Basiri et al. 2021; Kwan and Lim 2020; Mansoor et al. 2020). Some studies investigated tweets from different countries; however, an analysis of tweets about these countries is extremely limited (for an example, see Lee and Kim 2021). Tweets about countries are regarded as word-of-mouth communications that influence a country’s brand image and reputation; these important issues are widely discussed in the academic field of place branding.

The effect of Twitter on country brands during the pandemic

Countries should pay attention to the discourse manifested on social media platforms because their media representation is pivotal to external recognition and their self-identity in the world system (Wu et al. 2016). Academic studies of country representation and identity are eminent in the field of place branding, which is defined as a process that focuses on people’s perceptions of a place (Kavaratzis 2004). Places on all levels including but not limited to towns, cities and countries possess a brand—or a network of association in people’s minds based on the visual, verbal and behavioural expressions of a place (Zenker and Martin 2011).

During and after crises, typically negative portrayals of countries in the media affect their brand image and reputation. Negative reputations are known to suppress the supportive behavioural intentions of stakeholders (Coombs 2007). Therefore, it is imperative for countries to understand the extent to which crises impact their brand image and reputation and come up with appropriate strategies.

Many image crises of countries have been widely studied. Figure 1 depicts various types of crises based on temporal and geographical scales. The y-axis indicates the temporal scale of the crisis ranging from sudden image crises that span multiple excruciating days to prolonged cumulative crises that last multiple years if not decades (Avraham and Ketter 2008). The x-axis portrays the geographical scale of the crisis from national (or smaller) to global levels.

Sudden image crises in a country (bottom left corner of Fig. 1) include terrorist attacks, accidents, crimes or violent acts and natural disasters. Examples of such crises that negatively impacted the image of a country include the earthquake in Nepal (Ketter 2016) and the capsizing of a tourist speedboat in Thailand (Taecharungroj and Avraham 2022). Some crises may also have a wider impact outside the country of origin. For example, the Charlie Hebdo attack in France led to a major discourse surrounding religious tensions in Europe (Smyrnaioi and Ratinaud 2017). A country may face a prolonged crisis that spans years (top left corner of Fig. 1) such as multiple disasters in Haiti (Seraphin et al. 2016), the Jyllands-Posten Cartoon crisis in Denmark (Rasmussen and Merkelsen 2014) and war, terror and violence in Israel (Avraham 2009).

Crises that take place on a regional level affect the public images of many countries simultaneously. For example,
the Ebola epidemic tarnished the images of West African countries such as Liberia and Sierra Leone (Avraham and Ketter 2017), while the ongoing refugee crisis has adversely affected the image and reputation of European countries, leading to negative consequences and diverse governmental responses (Ivanov and Stavrinoudis 2018; Pamment et al. 2017). Large-scale natural disasters such as earthquakes and tsunamis occur and end abruptly causing devastation on a regional scale, while economic or financial crises also have regional impacts and span multiple years. For example, the European debt crisis has negatively undermined many macroeconomic indicators and tarnished the reputation of countries such as Portugal, Spain and Greece. However, despite overall decline in the economy, tourism sectors in these countries have remained largely intact (Brito 2014; Costa et al. 2014; Leiva-Soto 2014) because the crisis did not alter tourists’ perceptions of risks and safety (Li et al. 2018).

Pandemics such as COVID-19 are rare events that span multiple years and affect countries on a global scale (top right corner of Fig. 1). One region that has been devastated by the COVID-19 pandemic is SEA. Eighteen months after the first detected case in the region in January 2020, 7,307,287 cases and 147,973 deaths have been recorded in SEA. Countries in SEA have followed diverse paths during the pandemic (Regan 2021). The two high-income countries in the region, Singapore and Brunei, have coped well since the beginning, whereas Indonesia and the Philippines were devastated by the pandemic in the mid-2020s and the situation had since deteriorated. From being regarded as an initial success story (Beech 2021; Chai 2021; Yen et al. 2021), Thailand, Malaysia and Vietnam have seen massive increases in cases and deaths in 2021. Cambodia and Laos—the poorer countries in SEA—have managed to control the spread of COVID-19, whereas Myanmar has suffered a double disaster of public health and political crises.

Despite its severity, a comprehensive understanding of the effects of the COVID-19 pandemic on country image remains limited. A detailed elucidation can allow comparison of the effects of the pandemic with other image crises. To address the research gaps and scope, three RQs were posited.

**RQ1** What are the topics of tweets about SEA countries during the COVID-19 pandemic and how do they change over time?

**RQ2** How do sentiment levels of tweets about SEA countries change over time during the COVID-19 pandemic?

**RQ3** How do emotions of tweets about SEA countries change over time during the COVID-19 pandemic?

Providing answers to these three research questions can contribute to and deepen the understanding of country brands and communications during crises. The existing literature demonstrates that crises deteriorate country brand images (e.g. Ivanov and Stavrinoudis 2018) through negative portrayals on international media channels (Avraham 2015) as part of the process known as “place communications”. Effective place communications are important because they affect the image of countries and their attractiveness in the minds of the stakeholders (Braun et al. 2014; Kavaratzis 2004).

Kavaratzis (2004) separated place communications into three types as primary (actions), secondary (official communications) and tertiary or word-of-mouth (WOM) communications. Tertiary WOM communications are defined as uncontrollable, informal and often unintentional communications among consumers, the media and competitors (Hanna and Rowley 2011; Zenker and Braun 2017). WOM communications have been amplified and become highly credible and influential in the era of digital and social media. WOM communications are crucial in place branding. Place brands are not controlled by a single entity but co-created by a multitude of people who appropriate them over time (Kavaratzis and Hatch 2013). WOM communications represent and express the identity of the place, (Kalandides 2011; Taeharungroj 2019), shape the image of the country and ascribe its meaning in the minds of the communicators and their audiences (Andéhn et al. 2014; Kavaratzis and Hatch 2021). WOM communications on social media platforms have dominated information exchange during recent crises (Avraham 2018; Ketter 2016).

Existing literature assessing the characteristics of WOM communications during crises is limited. Hanna et al. (2021) posited that understanding the social media impacts on place brands both in-the-moment and over the longer term is scarce and needed. This research answered the three research questions and contributed to the overarching research gap concerning the role of WOM communications in the place branding process.

**Methodology**

**Data collection and pre-processing**

The research process began with data collection and pre-processing (Fig. 2). Data from 22 January 2020 to 31 July 2021 totalling more than 1.7 billion tweets related to the COVID-19 pandemic were collected from the dataset curated by Chen et al. (2020). Ten percent of tweets daily were randomly selected. In total, 175 million tweets were extracted and downloaded using Hydrator. Tweets containing the names of the 10 countries were screened and 359,085...
remained. Duplicated, non-English tweets and retweets were removed. Words in tweets were lemmatised using the “text-stem” package and stemmed using the “SnowballC” package in R. Stop words were removed from the tweets. Stop words included (1) generic words from the “tidytext” package, (2) common words such as “corona”, “covid” and “virus”, (3) names of the ten countries and (4) frequently used hashtags such as “#WhatsHappeningInMyanmar”. The final dataset contained 115,553 tweets.

Topic modelling using LDA

This study used LDA, an unsupervised machine learning, topic modelling algorithm to reveal topics in the corpus of COVID-19 tweets about Southeast Asian countries. LDA uses the co-occurrence of words to assume the existence of a hidden structure in the dataset (Blei et al. 2003; Tirunillai and Tellis 2014). It creates a three-level Bayesian probability model, where each tweet represents a probability distribution over a topic and each topic represents a probability over words.

Before performing LDA, the number of topics and corpus-level hyperparameters, alpha (α) and beta (β) must be specified. To determine the optimal number of topics in the corpus of tweets, this study used two techniques from the open-source package in R language “LDATuning”. Results in Fig. 3 indicated 12 as the most suitable number of topics because this achieved the minimal average distance of topics according to an algorithm by Cao et al. (2009).

Hyperparameter tuning and the LDA algorithm were performed using the “topicmodels” package in R. Three levels of alpha (1, 0.1 and 0.01) and three levels of beta (0.1, 0.01 and 0.001) were tested to indicate the model with the lowest perplexity score, implying better generalisation performance (Blei et al. 2003). From six combinations, the model of alpha = 0.1 and beta = 0.001 was selected. LDA was performed using the Gibbs sampling method (Tirunillai and Tellis 2014). The topics were then extracted, with each topic containing 15 most representative words for interpretation and naming.

The LOESS smoothing function was fitted to visualise the monthly trends of tweets by topic from January 2020 to July 2021. Such trends were later used to identify topical themes. An alluvial plot (the “ggalluvial” package in R) was used to visualise both the volume of tweets and the rank of topics across a 19-month period in each country. Alluvial plots display monthly rankings of tweets by topic frequency. The ribbon width represents the number of tweets on each topic in each month. The most common topic of each month was placed at the top with the least common at the bottom. These plots elucidated the prevalence and evolution of topics in each country during the course of the pandemic.
VADER sentiment analysis

The sentiment of each tweet was analysed using an open-source Valence Aware Dictionary for Sentiment Reasoning (VADER) algorithm (Hutto and Gilbert 2014). VADER is a lexicon and rule-based sentiment analysis tool that can detect the intensity of both positivity and negativity in tweets. Compared with other techniques, VADER is unique because it considers punctuation, capitalisation, degree modifiers, the contrastive conjunction (but) and negations in addition to a large library of words. VADER became popular after Hutto and Gilbert (2014) demonstrated that the algorithm was superior to many other conventional tools and techniques for analysing social media texts, online reviews and editorials. VADER sentiment analysis was performed using the “vader” package in R; the algorithm produced a compound sentiment score of every tweet on a scale of −1 (most negative) to 1 (most positive) based on the composition of negative, neutral and positive words in a tweet. Sentiment scores of tweets about each country were computed to indicate average monthly levels. The LOESS smoothing function was fitted to visualise the trends.

NRC emotion lexicon

To identify the emotions in tweets, this research used NRC Emotion Lexicon (EmoLex), which contains more than 10,000 word-sense pairs (Mohammad and Turney 2013). NRC EmoLex has 8 primary emotions as anger, anticipation, fear, surprise, sadness, joy, disgust and trust. The experiment found that the word pairs in NRC EmoLex corresponded well with the annotations of trained human judges (Mohammad 2012). In this study, NRC emotions in tweets were detected using the “syuzhet” package in R. Total emotion counts in each month were computed to indicate the number of words that elicited each emotion in each tweet. Results were visualised using alluvial plots to indicate prevalence and changes in monthly emotion counts in each country during the course of the pandemic.

Results

After data collection and cleansing, 115,553 tweets remained for further analyses. From the final dataset, Myanmar had the most tweets (19,337), followed by Singapore (18,819), the Philippines (17,807), Malaysia (17,101), Thailand (14,981), Vietnam (14,879), Indonesia (14,122), Cambodia (3,970), Laos (931) and Brunei (465). Figure 4 presents the number of monthly tweets by country. Countries with the most tweets in each month were placed at the top while those with the fewest tweets were at the bottom. Results showed that the number of tweets about SEA countries surged at the beginning of the pandemic in February when cases were first detected in the region. The number of tweets fell during a relatively dormant period in March and April 2020 when
attention turned to other regions in the world. The number of tweets about SEA countries rose again in June and July 2020, coinciding with the rising cases in the Philippines and Indonesia. Most notably, Fig. 4 illustrates a spike in tweets about Myanmar from February 2021 that peaked in July 2021. LDA topic modelling was performed to deepen the understanding of the discourse about countries and to answer RQ1.

LDA results

LDA produced 12 distinct topics from 115,553 tweets. Table 2 presents the most representative words of each topic, examples of tweets and the trend that connotes the number of tweets about that topic from January 2020 to July 2021. According to the trends, the 12 topics were separated into three themes.

The first theme of topics was early discourse, which included travel and countries. Tweets about travel occurred early in the pandemic when the most salient impact was travel restrictions such as banning flights from Wuhan and China, quarantining cruise ships and reporting about affected travellers throughout the world. This topic gradually faded when travel restrictions became the norm and ubiquitous. Another topic in this theme was countries; it included tweets that ranked countries by their cases, deaths or how well they responded. In the early stage, many tweets listed countries where COVID-19 cases were detected. This topic gradually faded when the situation became global.

The second theme of topics was a parallel discourse that rose and fell in relation to the severity of the pandemic. Topics in this category included politics, protection, hope, death, economy and lockdown. These topics rose and peaked in January 2021 when the number of cases reached the first regional peak. They then slightly decreased between February and May 2021 when the situation was seemingly under control in most countries. Later, the number of tweets regarding these topics rose sharply when the situation deteriorated from May to July 2021. Politics as a topic of tweets usually criticised the government for their poorly perceived mismanagement. Protection in tweets concerned personal protective equipment (PPE) such as face masks and preventive measures such as social distancing. Hope was a distinctly positive topic that involved people tweeting hopeful messages during the pandemic. Such tweets often expressed their feelings while staying at home, nostalgic thoughts and activities that they loved and missed. Death as a topic of tweets reported casualties and the number of cases in each country. Lockdown involved tweets about government measures to lockdown the city or to close borders to counter the rising cases. Finally, tweets about the business and economic impacts were placed in a topic called economy.

The third theme of topics was late discourse, which included military, variant, vaccine and healthcare. These four topics were either low in intensity or absent at the beginning of the pandemic. However, the number of these topics rose sharply in 2021 because of various reasons. The Military topic exclusively involved the military Coup d’etat in Myanmar on 1 February 2021. Vaccine and variant topics emerged in late 2020 when new effective vaccines were approved and new mutated variants of COVID-19 appeared in the UK and India. Healthcare tweets included those that described the tasks of healthcare workers such as testing, contact tracing, treating and quarantine. This topic intensified when the number of cases in SEA overwhelmed the capacity of medical facilities and personnel in 2021.

Findings showed that various public discourse emerged and evolved during the course of the pandemic. Some discourse emerged early and faded; some rose and fell in relation to the severity, while some occurred because of new situations.

To understand how each topic emerged and changed in each country, alluvial plots of the topics by country were visualised (Fig. 5). Figure 5 illustrates the multiplicity of public discourse in each country and the divergent paths. The discourse on Twitter about Indonesia was mainly about the economy until September 2020 when protection became a hot topic because local officials ordered eight people who violated the mask mandate to dig graves for COVID-19 victims. This news about Indonesia spread worldwide. When cases in Indonesia rose rapidly in 2021, topics about healthcare and the failure to cope with the situation emerged, followed by death and variant in July 2021 when the situation reached a peak.

Two counties that shared a relatively similar COVID-19 trajectory—Malaysia and Thailand—had divergent discourse on Twitter. Two topics dominant in Malaysia were politics and hope. From the mid-2020s until the peak in July 2021, political tweets blaming the government and offering support and hope to fellow citizens during the stay-at-home period were evident. By contrast, lockdown discourse was dominant in Thailand due to its renowned service industry, while information about vaccines surged strongly in 2021.

The Philippines was hit by the pandemic early. Discourse on Twitter mainly concerned death from the mid-2020s when many people reported COVID-19 cases and deaths in the country. Interestingly, a topic of hope also appeared at the same time. When the situation in the Philippines deteriorated in 2021, public discourse about vaccines dominated. By contrast, as a financial and business hub in the region, travel discourse of Singapore rose sharply at the beginning of the pandemic. Contrary to many other countries in the region, the pandemic situation in Singapore has not been aggravated. Thus, the topic most publicly discussed was the economy. Despite the low number of cases in Singapore,
| Topic \((n)\) | Representative words | Examples of tweets | Trend (Jan20-Jul21) |
|----------|----------------------|--------------------|--------------------|
| Travel (7866) | Travel, China, flights, test, Wuhan, ban, quarantine, arrived, ship, Chinese, day, positive, airlines, passengers, cancelled | "As per update received from Singapore Airline: Airline will waive all cancellations and change fees for customers with tickets issued on or before 28 January 2020" | "My flight is scheduled on March 1 which I want to cancel due to the current coronavirus situation in Thailand" |
| Countries (7411) | China, India, Taiwan, Japan, Korea, South, Australia, UK, deaths, (New) Zealand, world, USA, population, lockdown, million | "UPDATED confirmed #coronavirus cases: Thailand Japan Hong Kong Singapore Taiwan Australia Malaysia Macau..." | Ranking of national responses to COVID: In the top 10: Asia 4 nations: Vietnam, *Taiwan, Thailand...* |
| Politics (12,288) | War, people, Americans, died, Trump, world, deaths, government, killed, lives, lost, time, decision, worse, fight | @realDonaldTrump COVID-19 has killed more than the Vietnam War | "Malaysia is at war, but the generals only focus on political battle rather than combat COVID-19" |
| Protection (10,274) | Mask, people, wear, social, stay, lockdown, home, distancing, school, students, safe, time, children, live, lives | "#Robots are patrolling parks in #Singapore reminding people to practice social distancing" | "People without masks forced to dig graves for victims in Indonesia" |
| Hope (10,061) | Stay, hope, lockdown, home, day, love, safe, time, I'm happy, family, visit, lives, friends, miss | Living in multi-racial Malaysia, we celebrate every festival. Missing visits by the lion dance to my home" | "I hope when this pandemic ends we can attend your concert here in the Philippines again" |
| Death (10,094) | Deaths, reports, total, infections, record, day, daily, confirmed, update, health, recovered, rate, active, toll, rise | "Indonesia reports a record third consecutive day of 24,836 new cases and a record fourth consecutive day of 539 deaths from COVID-19" | "The Philippines logs 7255 additional coronavirus cases on Monday, May 3" |
| Economy (11,559) | Business, economy, economic, impact, support, crisis, market, bank, global, amid, government, recovery, job, response, industry | "Impact of COVID-19 on Farmers Laos—Houan Oun organic vegetable group" | The Singapore Dollar fell against the US Dollar as USD/SGD... |
| Lockdown (8048) | Lockdown, restrictions, travel, city, outbreak, close, measures, border, Bangkok, reopen, government, week, surge, amid, day | "Thailand announces tighter restrictions in the capital Bangkok and nine provinces on Friday in an effort to slow the spread of the coronavirus" | "Vietnam’s economic hub Ho Chi Minh City began a two-week lockdown on Friday" |
| Military (14,277) | Military, junta, people, oxygen, protest, coup, weapon, strike, terrorists, dictatorship, SAC, civilians, killed, village, Mandalay | "Medical professionals in Myanmar are shot, beaten and arrested for SAVING LIVES" | "Protect Against Myanmar Military rule across the Country. Cover the face of Fear of killing or arrest" |
| Variant (8592) | Variant, health, spread, India, strain, outbreak, detected, time, Vietnamese, China, Delta, UK, Chinese, infections, world | "Vietnam detects highly contagious new coronavirus variant as infections surge" | "Experts in India have found a variant more infectious than Delta. Malaysia is vigilant" |
| Vaccine (7712) | Vaccine, doses, million, China, received, Sinovac, minister, government, president, health, AstraZeneca, approved, national, PM, trials | "The #Philippines has signed a supply agreement for 40 m doses of the COVID-19 vaccine developed by Pfizer and BioNTech" | "#Thailand is negotiating with Chinese #vaccine manufacturers to increase the purchase of #COVID-19 vaccines" |
there was an evident spike in the variant topic during May 2021. In May 2021, an Indian news outlet accused Singapore of being the origin of a new “Singapore variant”, which the Singaporean Government quickly refuted as “fake news” (Jain 2021). Similarly, tweets about a variant in Vietnam also surfaced in May and June 2021 out of the fear that a new variant had appeared in the country. However, this was ruled out by the WHO (Onishi, 2021). A dominant public discourse about Vietnam was politics from the mid-2020s. Surprisingly, tweets were mainly aimed at Donald Trump who allegedly mishandled the COVID-19 situation in the US. Tweets often compared the deaths of Americans during the pandemic with those who died during the Vietnam War (among others) to illustrate the failure of the US Government. The number of tweets decreased significantly after Donald Trump lost the election at the end of 2020. However, discourse using the Vietnam War to politically attack an opponent remained until July 2021.

Myanmar had arguably the worst situation in SEA. The country suffered from a healthcare crisis and also a political crisis after the coup in February. Public discourse about the pandemic and Myanmar exclusively concerned criticism of the military government. The narrative was primarily about the violent government measures towards the opposition, the struggle of protesters amid political oppression and the seriousness of the pandemic.

**Sentiment of tweets about countries**

To answer RQ2, the average sentiment level (from the most negative — 1 and the most positive +1) of tweets about each country in each month was calculated using VADER. Figure 6 displays the smoothened results of the sentiment analysis, while Table 3 shows the average level of sentiment and emotion counts of tweets for each topic. Most SEA countries started with neutral or slightly negative sentiment towards the pandemic and this continually improved owing to the rise of the hope discourse. Hope was the only strongly positive discourse of this pandemic (0.32), while the economy was a distant second (0.13) (Table 3). Results demonstrated that the messages of hope lifted the sentiment of countries in SEA. However, sentiment levels of most countries decreased in 2021 due to the rise of less positive discourse topics such as death, variant and lockdown. The exceptions were Myanmar which received an overwhelming volume of negative military tweets and Vietnam, which recorded a high number of negative tweets about politics from the early stage of the pandemic.

**Emotions in tweets about countries**

NRC EmoLex was performed to detect the emotions in tweets to answer RQ3. Figure 7 illustrates the emotion
counts per month by country. For most countries, fear and trust were the most dominant emotions during the course of the pandemic (Table 4). Fear was represented in tweets about the danger of the pandemic and the harm that it inflicted. Trust was elicited in tweets that expressed stability, strength, calmness and assurance. The trust emotion was
often found in tweets that reported on government actions or plans. The third and fourth most common emotions were anticipation and sadness. *Anticipation* appeared in tweets that discussed the future as typically uncertain during the pandemic. Tweets that elicited *sadness* contained words that expressed remorse, sorrow and hopelessness. Myanmar presented a unique case where tweets about military oppression strongly projected the two emotions—*anger* and *surprise*. These findings implied that emotions could change based on evolving discourse on Twitter. Table 4 shows descriptive statistics of the topics, sentiment and emotions of the ten countries.

### Discussion and conclusion

The first research objective was to identify the multiplicity of public discourse on Twitter concerning ten countries in SEA. LDA was performed with 115,553 tweets to identify 12 topics as military, politics, protection, hope, death, variant, economy, healthcare, lockdown, vaccine, countries and travel. Topics were grouped into three themes spanning the course of the pandemic as early, parallel and late discourse. For the second objective, this research found that sentiment improved with increasing numbers of tweets.
Fig. 7  Monthly emotion counts (NRC EmoLex) by country
of hope and fell when negative narratives predominated. Finally, the four prevalent emotions during the pandemic were fear, trust, anticipation and sadness, except for Myanmar where anger rose intensely after the coup. Compared with the existing literature, this research explored and elucidated how topics emerged and evolved in the context of the ten SEA countries. Investigation of the evolution of the topics was previously undertaken by Valdez et al. (2020). However, here, the timescale was expanded and the findings were contextualised with the perceptions about each country.

Compared with other types of crises, our results suggested that pandemic impacts on country images are **phased** and **pervasive**. Unlike prolonged crises such as the ongoing conflict in the Middle East (see Avraham 2009) which has no end in sight, the COVID-19 pandemic is more akin to shorter crises that have clear separate phases (Rasmussen and Merkelsen, 2014). This research identified topics of tweets that emerged and evolved in three main phases/themes. The first phase called *early discourse* included topics that began with the pandemic such as travel restrictions and listings of countries that detected COVID-19 cases and deaths. The second phase—*parallel discourse*—rose and fell with the severity of the pandemic, while *late discourse* included topics that emerged in 2021 such as vaccine, variant and military. Our results align with Avraham and Beirman (2022) who identified multiple phases of communications from the perspectives of government officials during the pandemic.

The findings of this research confirmed that the overall sentiment at the beginning of the pandemic was negative (Boon-Itt and Skunkan, 2020) and improved over time (Chandrasekaran et al. 2020; Kwan and Lim 2020). The improvement of sentiment in tweets was the result of the increase in tweets about *hope* as people stayed at home and adjusted to the “new normal” lifestyle. However, the sentiment turned sharply negative when new variants hit SEA countries and topics such as *lockdown*, *healthcare* and *variant* then dominated public discourse. Such rises and falls in emotions and discourse were also present in sudden crises (e.g. Gascó et al. 2017). However, due to the longer timeframe, there were more fluctuations in emotions and

### Table 4: Descriptive statistics

| Item       | Brunei | Cambodia | Indonesia | Laos    | Malaysia | Myanmar | Philippines | Singapore | Thailand | Vietnam | Total  |
|------------|--------|----------|-----------|---------|----------|---------|-------------|-----------|----------|---------|--------|
| No. tweets| 465    | 3970     | 14,122    | 931     | 17,101   | 19,337  | 17,807      | 18,819    | 14,981   | 14,879  | 115,553|

| Topics (% of the total)        | Brunei | Cambodia | Indonesia | Laos | Malaysia | Myanmar | Philippines | Singapore | Thailand | Vietnam |
|--------------------------------|--------|----------|-----------|------|----------|---------|-------------|-----------|----------|---------|
| Military                       | 1%     | 2%       | 2%        | 1%   | 1%       | 67%     | 1%          | 1%        | 2%       | 1%      | 10%    |
| Politics                       | 3%     | 7%       | 9%        | 11%  | 11%      | 6%      | 11%         | 6%        | 7%       | 27%     | 11%    |
| Protection                     | 3%     | 8%       | 11%       | 13%  | 10%      | 4%      | 9%          | 10%       | 10%      | 8%      | 9%     |
| Hope                           | 16%    | 3%       | 10%       | 7%   | 15%      | 2%      | 14%         | 6%        | 9%       | 5%      | 9%     |
| Death                          | 21%    | 11%      | 11%       | 7%   | 12%      | 3%      | 12%         | 7%        | 10%      | 6%      | 9%     |
| Variant                        | 3%     | 7%       | 8%        | 10%  | 8%       | 2%      | 7%          | 10%       | 7%       | 10%     | 7%     |
| Economy                        | 6%     | 14%      | 13%       | 11%  | 12%      | 3%      | 10%         | 14%       | 8%       | 9%      | 10%    |
| Healthcare                     | 3%     | 6%       | 7%        | 4%   | 7%       | 3%      | 6%          | 10%       | 8%       | 4%      | 6%     |
| Lockdown                       | 5%     | 10%      | 8%        | 9%   | 7%       | 2%      | 6%          | 7%        | 14%      | 6%      | 7%     |
| Vaccine                        | 7%     | 12%      | 8%        | 7%   | 7%       | 2%      | 12%         | 5%        | 8%       | 4%      | 7%     |
| Countries                      | 16%    | 9%       | 7%        | 16%  | 5%       | 3%      | 6%          | 10%       | 8%       | 15%     | 6%     |
| Travel                         | 17%    | 11%      | 6%        | 4%   | 6%       | 2%      | 6%          | 14%       | 9%       | 5%      | 7%     |
| 100%                           | 100%   | 100%     | 100%      | 100% | 100%     | 100%    | 100%        | 100%      | 100%     | 100%    | 100%   |

| Average VADER sentiment score (from −1 to 1) | 0.11  | 0.03  | 0.01 | 0.08 | 0.07 | -0.17 | 0.06 | 0.06 | 0.05 | -0.07 | 0.00 |
| Percentage of NRC emotion to the total counts | Anger | 6%    | 9%   | 9%   | 9%   | 9%   | 9%   | 21%  | 8%   | 8%   | 8%   | 10%   | 12% |
|                                              | Anticipation | 17%  | 17%  | 15%  | 15%  | 17%  | 10%  | 15%  | 17%  | 17%  | 17%  | 14%   | 14% |
|                                              | Disgust      | 4%   | 5%   | 6%   | 6%   | 6%   | 6%   | 5%   | 5%   | 6%   | 7%   | 6%    | 6%  |
|                                              | Fear         | 19%  | 18%  | 20%  | 17%  | 18%  | 21%  | 20%  | 19%  | 18%  | 21%  | 20%   | 20% |
|                                              | Joy          | 11%  | 10%  | 10%  | 10%  | 11%  | 5%   | 10%  | 10%  | 10%  | 8%   | 9%    | 9%  |
|                                              | Sadness      | 13%  | 13%  | 15%  | 14%  | 13%  | 12%  | 15%  | 13%  | 13%  | 15%  | 13%   | 13% |
|                                              | Surprise     | 6%   | 7%   | 7%   | 7%   | 7%   | 14%  | 7%   | 7%   | 7%   | 7%   | 9%    | 9%  |
|                                              | Trust        | 24%  | 22%  | 19%  | 21%  | 20%  | 11%  | 20%  | 21%  | 20%  | 17%  | 17%   | 17% |

100% 100% 100% 100% 100% 100% 100% 100% 100% 100% 100% 100%
sentiment depending on how events unfolded during the COVID-19 pandemic.

The effects of the pandemic proved pervasive. Unlike large-scale regional crises such as the European debt crisis that only affected the business aspect of country images or the small-scale capsized boat crises in Thailand that only affected tourism, the COVID-19 pandemic negatively impacted all groups of place customers including tourists, residents and businesses. Tourists were concerned about safety (as portrayed in death) and travel restrictions (travel and lockdown), while residents were affected by the new variants, the collapse of the healthcare system, the lack of protection and hope. The main discourse topics undermining business were economy and military. The pervasive effects on all place customers and long fluctuating phases made the COVID-19 pandemic different from other image crises.

**Theoretical contributions to place branding**

In the theory of place branding, it is widely accepted that WOM communications shape the place brand image (Braun et al. 2014; Kavaratzis 2004). However, “how” this happens is largely unknown. The analytical techniques used in this research helped to deepen the understanding of WOM communications and allowed the researchers to delve into WOM communications of countries on Twitter during the COVID-19 pandemic. Figure 8, (adapted from Kavaratzis and Hatch 2013), illustrates the role of WOM communications during the pandemic and depicts the interplay of place identity, image and WOM communications.

WOM communications represent the identity of the place (Kalandides 2011; Taecharungroj 2019) in the process referred to as “impressing” (Kavaratzis and Hatch 2013). The pandemic occurred on a global scale but perceptions of individual countries varied significantly depending on both internal and external factors. The associations, events and situations in a particular country are manifested through country identity including its institutions, personality, people’s behaviours, experiences, media representation and physical features (Taecharungroj 2019). Such local instances communicated on Twitter influence the tweets from different countries (Basiri et al. 2021; Kwan and Lim 2020; Mansoor et al. 2020) and simultaneously and gradually shape their images. In addition to the cognitive aspect of the countries, WOM communications also elicit a complex mixture of negative (fear and sadness) and positive (anticipation and trust) emotions. Although fear was found as the leading emotion from the analysis of tweets, other emotions such as anticipation, trust and sadness (empathy) were also evident.

False WOM communications during a crisis may shape a negative image of the country. Diffusion of misinformation, false information and controversial narratives (e.g. “Chinese virus”—also referred to as a parallel pandemic or infodemic (Boulos and Geraghty 2020; Budhwani and Sun 2020)—are major concerns of officials (Hagen et al. 2018). Failing to acknowledge and combat misinformation or information not supported by evidence allows falsehoods to spread and causes harm (Young et al. 2018). Nevertheless, WOM communications are largely uncontrollable; some associations are difficult to avoid. For example, “Vietnam” and the historical Vietnam War have been used widely as a political narrative by US citizens who compared the deaths caused by government actions (or inactions) during the pandemic with casualties in the past wars. This public discourse during the pandemic in the US about Vietnam is not relevant to the present situation in the country. However, it may prolong the negative image of the country in the minds of international audiences.

Not all impressions last long and are significant enough to be mirrored as a country’s identity. The two important factors are longevity and intensity. Some impressions from WOM communications do not last long; they occur, may even spike but eventually fade. For example, Singapore had a spike in the number of tweets in May 2021 after an Indian media outlet reported a possible “Singapore variant”. This led to a high volume of tweets and counter-tweets from many sides. Similarly, news about a possible “Vietnam variant” also surfaced between May and June 2021, contributing to a high volume of tweets. In both cases, scientific evidence quickly debunked the claims and the topics faded during the following months. Nevertheless, some impressions are long-lasting such as the aforementioned example of the “Vietnam War” association. The infoveillance technique methods demonstrated in this research help countries track their WOM communications and identify the impressions that may remain over time.

The other key factor that strengthens the emergent images of the country is the intensity of WOM communications. Despite some variations, most countries in SEA share common problems: travel restrictions, incompetence of the public sector, lack of protective equipment, healthcare struggle,
declining economy and new variants. Thus, it is possible
that these common negative images may not stick to any
country because most of the grave events and situations are
relatively common. This is perhaps a paradoxical feature of
the COVID-19 pandemic that countries face unbearable cir-
cumstances; however, because they all suffer, these negative
instances may not be permanently construed as part of their
images. By contrast, distinctively intensive instances during
the crisis may leave a strong permanent impression on the
image of a country. A clear example of such an instance is
the coup d’état on 1 February 2021 in Myanmar that drasti-
cally turned public discourse about the pandemic and Myan-
mar extremely negative.

Before the coup, tweets about Myanmar and the pandemic
were among the lowest in the region. The coup happened
during a time when the region was the most vulnerable, due
to the new infectious Alpha and subsequently Delta variants.
The situation in Myanmar can be referred to as a double dis-
aster or a double crisis of political upheaval that has brought
the country to the verge of civil war and a once-in-a-lifetime
pandemic (Ghosh 2021). UNDP (2021) projected that nearly
half of the population in Myanmar might be living in poverty
by 2022. Narratives about the political struggle merged with
feelings of hopelessness amid the pandemic. As a result,
anger and fear were the strongest two emotions in tweets
about Myanmar, while joy was by far the least among the
ten countries.

Indeed, this pandemic has devastating impacts on every
facet of life worldwide but the double disaster in Myanmar
has projected a considerably worse image of the country
on Twitter both qualitatively (topics, sentiment and emo-
tions) and quantitatively (volume of tweets). Such an intense
long-lasting negative image becomes mirrored as the distinct
identity of the country.

Research limitations and future research

Despite the contributions, this study had some limitations.
First, notwithstanding their pervasive use and increasing
penetration worldwide, Twitter users do not represent the
population at large. Second, the research dataset was ran-
donised (10%) from the original dataset to maximise effi-
ciency and speed. Although clear trends and implications
were indicated, analyses of the full dataset may yield dif-
ferent results. Another limitation was the language barrier.
This research analysed tweets in English for consistency and
standardisation across the region. However, most people liv-
ing in the region do not use English as their first language.
Future research should include and compare topics and sen-
timent of the various languages used by the endemic popula-
tion. Other avenues for future research include comparing
WOM and other types of communications during crises and
their relationships, the connection between expressions in
tweets and place identity and the long-term effect of WOM
communications on country reputation.

Policy implications and conclusion

Countries must pay attention to the discourse manifested on
social media platforms because their media representation
is pivotal to external recognition and their self-identity in
the world system (Wu et al. 2016). WOM communications
help shape the image of a country, with the eventual identity
mirroring intense and long-running images. Key actions for
public health and public relations officials are proposed as
follows:

Key action 1 Establish a digital infoveillance system: It
is essential for responsible agencies to adopt a public-
centric perspective on crisis communications (Zhao et al.
2018). The approach outlined here should be part of the
digital surveillance system that public health and public
relations officials use to analyse inconsistent, ambiguous,
contradicting, emotional and overly abundant messages
on social media during the pandemic. The ability to ana-
lyse conversations on social media platforms and catego-
rise them helps agencies to combat harmful misinformation
during the crisis (Guidry et al. 2017).

Key action 2 Detect intense changes and long-running
patterns: Temporal variation and formation of narra-
tives and sentiment are crucial for understanding public
discourse about the pandemic (Lyu and Luli 2021). The
results suggested that the characteristics and evolution of
online narratives during the course of the pandemic in
each country were heterogeneous and varied markedly
depending on local events. Public health and commu-
nications officials must be vigilant and monitor changes
in online narratives that could worsen or complicate the
situation during this long-running multi-faceted crisis.

Key action 3 Implement appropriate responses: Govern-
ment officials must design appropriate communication
strategies that effectively respond to emerging narratives
and sentiment. According to the findings, countries that
dealt effectively with falsehoods utilised credible scient-
ific evidence. Existing literature on crisis communica-
tions typically outlines several communication strategies
that can be used to tackle the crisis (Benoit 1997; Coombs
2007; Ketter and Avraham 2021). Evaluation of the effec-
tiveness of various communication strategies should be
conducted to continually improve the established system.

Success of public diplomacy and branding depends on
how the country responded to the pandemic (Lee and Kim
2021). Integration and synthesis of infoveillance tech-
niques will help public health and public relation agencies
to provide relevant information and initiate policies and
campaigns that correspond with the needs of the public (Chew and Eysenbach 2010). This research presented a set of infoveillance techniques that can detect immediate changes and visualise patterns of online narratives during a long-running multi-faceted crisis. Results shed light on the role of WOM communications that express the identity and shape the image of a country during times of crisis such as the COVID-19 pandemic.

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Data availability The processed dataset and R script can be accessed at github.com/viriyatae/pandemictweets. Alluvial and interactive line plots can be explored at viriyatae.shinyapps.io/pandemic_shiny/.

Declarations

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

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