The Australia Department of Foreign Affairs and Trade (DFAT) asked the RAND Corporation to conduct a proof-of-concept exploratory study using news and blog data to understand efforts by foreign countries to spread malign information regarding coronavirus disease 2019 (COVID-19) in the Indo-Pacific region. In this report, we define malign information as content that is provocative, inflammatory, possibly deceptive, or even untrue and that is disseminated or boosted for the purpose of advancing foreign countries’ strategic goals. DFAT asked RAND to use its proprietary lexical analysis platform, RAND-Lex, to explore whether news and blog data could provide some initial insights on the reach of, content of, and tactical strategies used in foreign malign information regarding COVID-19 in the Indo-Pacific.

Using NewsAPI, a database of global news and blogs, we developed a data pipeline and analytic flow that allows analysts to (1) identify key features of foreign malign information efforts and (2) track down specific foreign malign information campaigns. This allowed us to discover several key features of foreign malign information on COVID-19 in the Indo-Pacific and to identify an example malign information campaign.

**KEY FINDINGS**

- From November 2019 to August 2020, unreliable foreign channels pushed an outsized (per capita) amount of coronavirus disease 2019 (COVID-19) content towards small South Pacific islands, such as Fiji and the Solomon Islands.
- Known unreliable channels that engaged in COVID-19 messaging in the Indo-Pacific used emotional ‘hooks’, such as anger, to make their content stand out.
- Foreign malign information campaigns targeted Indo-Pacific diaspora members living in Western countries, sometimes by repurposing and amplifying original Western content.
A Needle in a Haystack: Finding Malign Information Efforts in COVID-19 News Reporting

Our first task was to create a sample of news and blog articles that included content that is relevant to the COVID-19 pandemic. We began by pulling a sample of all English-language news and blog articles in the NewsAPI data that were published between November 2019 and August 2020 and that contained the words ‘COVID’ or ‘coronavirus’ somewhere in the title or body of the article. This yielded approximately 4 million total articles.

We then limited our data set to articles that mentioned the following specific countries in the Indo-Pacific that are of interest to DFAT: Fiji, the Philippines, Singapore, the Solomon Islands, and Vanuatu. We used sets of keywords, including place names, famous individuals and celebrities from these countries, and other key terms to identify articles related to each country. This resulted in approximately 221,000 unique articles (see Figure 1). Finally, using a list of known unreliable news sources from Russia and China (see Appendix A), we searched the web addresses of each article in our data set. We identified 400 articles that were published by 15 unreliable news sources.

Why Analyse News and Blogs?

Much reporting on COVID-19 malign information has focused on social media. This analysis instead focuses on news and blog data because the efforts of such social media platforms as Twitter and Facebook to remove malign information make it more difficult to locate and trace the attempts of foreign actors and their nonstate partners to influence the COVID-19 information space. Thus, news articles and blogs, which are increasingly less censored and regulated than content on social media, present a data source in which malign information stays online and accessible for a comparatively longer time.

To help support the concept of a broad media search and data-indexing capability based on news topics, we selected a third-party data source provider, NewsAPI. The NewsAPI data source assisted us in supplementing media content by enabling access to full-text news articles and blog posts from more than 50,000 sources across 54 countries.

FIGURE 1
Finding COVID-19 Messaging and Malign Information in the Indo-Pacific

NOTE: We conducted an exploratory analysis using NewsAPI data to determine the amount of COVID-19 coverage for each country published by internal versus external sources. For the Philippines and Singapore, content published externally significantly outpaced internally generated content.
Where Are Foreign Actors Directing COVID-19 Malign Information?

We analysed the 400 COVID-19 malign information news and blog articles to determine the primary country referenced in each article by using the country names, place names, and other key terms mentioned in the previous section. The number of articles identified by country are presented in Figure 2. As shown in the figure, foreign malign information represents roughly the same proportion of content targeted towards small South Pacific Islands as was targeted towards the Philippines and Singapore when measured as a percentage of total articles about each country.4

It is difficult to know whether the amount of malign information we discovered (less than half a per cent of all articles) represents a threat. Our analysis was limited to known malign websites, which likely limited our ability to detect malign information propagated on other websites. Our analysis of a specific messaging campaign (which we discuss later in this report) revealed considerable replication across apparently novel (and temporary) websites. Thus, it is likely that our analysis has significantly underestimated the size and spread of foreign malign information regarding COVID-19 in the Indo-Pacific.

The Emotional Signature of Foreign Malign Information Efforts

We also analysed the emotional signature of COVID-19 coverage in the Indo-Pacific region. To do so, we used the stance capabilities in RAND-Lex. RAND-Lex’s stance analysis5 identifies attitudinal and cognitive linguistic variables (i.e., words and phrases), such as emotion, certainty or uncertainty, cultural values, and social closeness or distance, to help researchers understand how the world is being represented in text.6 RAND-Lex measures seven emotion variables in language (see Figure 3).

FIGURE 2
Targets of Foreign COVID-19 Malign Information

NOTE: This figure shows the number of articles from foreign malign information sources, by country. This represents 0.17 per cent, 0.21 per cent, 0.16 per cent, 0.26 per cent, and 0.27 per cent, respectively, of articles analysed from each country shown in the figure.
Using logistic regression analysis, we analysed the association between emotion—negativity, positivity, anger, fear, and sadness—and the likelihood that the article was from an unreliable source (see Figure 4). We found that unreliable sources were significantly more likely to include emotional content, particularly more anger and fear, and marginally more likely to include positivity. For example, a 1-percentage-point increase in the measured anger content of an article is associated with a 252 per cent increase in the likelihood of the article being from an unreliable news source.7 For more information, see Table B.1 in Appendix B.

To illustrate the role of negative emotion in malign information efforts, in Figures 5 and 6 we show example articles with relatively high and low

![Figure 3](image1.png)

**Emotional Stance Language Variables Measured by RAND-Lex**

- General negativity
  - Negative language that does not fall into the anger, fear, sadness, reluctance, or apology categories (e.g., “that sucks”, “suicidal”)
- Fear
  - Words referencing fear (e.g., “terrified”, “afraid”)
- Reluctance
  - Language indicating resistance in the mind (e.g., “regret that”, “sorry that”, “afraid that”)
- General positivity
  - All positive emotion language (e.g., “joy”, “wonderful”)
- Anger
  - Words referencing anger (e.g., “so mad”, “furious”)
- Sadness
  - Language expressing sorrow (e.g., “miserable”)
- Apology
  - Language meant to apologise (e.g., “I’m sorry”, “I have failed”)

![Figure 4](image2.png)

**Sentiment Overrepresented in News from Unreliable Sources**

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Percentage Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positivity</td>
<td>23</td>
</tr>
<tr>
<td>Negativity</td>
<td>66</td>
</tr>
<tr>
<td>Anger</td>
<td>252</td>
</tr>
</tbody>
</table>

NOTE: This figure shows the increased likelihood of an article being from an unreliable source given a 1-percentage-point increase in anger, negativity, and positivity language in RAND-Lex stance analysis.
In contrast, a sample article from a reliable news source, also targeting the Philippines, has relatively low negative emotion (0.61 per cent of the words were coded as anger, and 0.2 per cent were coded as general negativity) (see Figure 6). This difference in anger content is a powerful discriminator between news stories from reliable and unreliable sources.
Discovering a Specific Malign Information Campaign

We used the NewsAPI pipeline in combination with RAND-Lex to discover a specific malign information effort related to COVID-19. This discovery demonstrates how RAND-Lex—when it is paired with dynamic access to large-scale open-source news data—can function as a computational ‘prosthetic’ that an analyst can use to uncover significant linguistic features or trends across vast amounts of foreign news coverage. An analyst cannot ascertain these trends within a reasonable time frame by simply reading through these articles. With RAND-Lex, the analyst can more closely examine those features in context, conduct more-targeted data searches and analyses, and, ultimately, discover cases that appear to represent a specific foreign actor’s attempt to spread information in a malign and subversive way. This involves an iterative ‘human in the loop’ process of a human and machine interpreting data in sequence (see Figure 10 for the full process).

Using RAND-Lex to Understand COVID-19 Content from Countries with Strategic Interests in the Indo-Pacific

In the first stage of this analysis, we used three RAND-Lex analytic processes to get a sense of topics and themes that were overrepresented in COVID-19 articles from non-Western countries with strategic interests in the Indo-Pacific (China, India, Malaysia, and Russia) compared with articles from Australia and its close Western allies (United Kingdom, United States, and Canada). In constructing the exploratory analysis, we initially assumed that China, India, Malaysia, and Russia report in roughly equal proportion to Australia and close Western allies about various topics in the Indo-Pacific region in the context of COVID-19. We then constructed contrastive corpora that contained keywords relating to COVID-19 and the Indo-Pacific islands but that segregated articles by the source country. In other words, we were trying to create two comparative corpora about the same topic but from distinct sources. After creating these comparative corpora, we could generate useful, interpretable results using text-mining techniques from RAND-Lex’s analytic processes. The three techniques we used were keyness testing,\(^8\) collocate extraction,\(^9\) and topic modelling.\(^10\) Using these methods, we discovered that content on COVID-19 from countries with strategic investments in the Indo-Pacific contained a disproportionate amount of words related to drugs, drug shortages, and the country of Canada compared with Australia and its close Western allies.

Using Emotional Tone to Conduct a Focused Search

In the next stage of analysis, we used stance analysis, which we described in the previous section, to examine articles with the highest general negativity scores. Specifically, we manually inspected articles with the top 1 per cent of general negativity scores that originated from countries with strategic investments in the Indo-Pacific. One such article contained negative language related to an apparent shortage of therapeutic drugs for COVID-19 in Canada. The article explicitly referenced a group in Canada, the Critical Drugs Coalition, which wrote an open letter to the Canadian government regarding the shortage of key drugs. The letter also called for broad, sweeping, and immediate government intervention. Notably, keyness testing, collocate extraction, and topic modelling also identified keywords related to Canada and drug shortages.

As we examined the article, we discovered its source to be a known Chinese malign information website (People’s Daily), which credited the article to another such website (Xinhua) (see Figure 7). This motivated us to investigate further.

Leveraging Google Search Omitted and Demoted Results

To gain more understanding of the article’s content, we used segments of text from the original article to search for additional related results. Knowing that search engines, such as Google, often demote likely malign information from various websites,\(^11\) we explicitly required the search engine to provide all demoted and cached content for viewing.
Through this process, we verified that Canada did experience a drug shortage and that the Critical Drugs Coalition actually did write an open letter to Canada’s health minister. During this research process, we also uncovered an op-ed letter that appears to have first been published on 22 July 2020 on the Canadian state-run network CBC (i.e., a non-malign originating source). We noticed a few duplicate articles and then iterated the search for exact phrasing from this op-ed. However, as Figure 8 illustrates, through this process, search results indicated significant duplication of the narrative by foreign sources in mid-August 2020. In Figure 8, the red arrows point to all the websites that contain the duplicate text, despite having seemingly disparate website names and content. This wave of duplicated news articles contained headlines including ‘Pandemic Creating Potential for Drug Shortages that Canada Isn’t Equipped to Deal with’, ‘What Is Behind the Latest Increase in Coronavirus Cases in . . . ’, and seemingly disconnected headlines, such as ‘“Sitting Back and Watching”: Why Vulnerable Canadians Can’t Celebrate the Reopening’.

As we examined the duplicated content, we noticed that some of the additional commentary was
Conclusion, Limitations, and Future Directions

To support DFAT in identifying and addressing foreign malign information on COVID-19 in the Indo-Pacific, we developed a data pipeline and analysis process that identified key characteristics of malign information efforts and provided open-source analysts with the ability to identify specific malign information campaigns. Through the use of RAND-Lex and analyst-guided filtering of data obtained from NewsAPI, we identified distinct emotional signatures of malign information in the Indo-Pacific region that leverage anger and other negative emotions. In addition, we found a specific malign information effort that is relevant to the Indo-Pacific region and found to be directed at the Indo-Pacific diaspora in Ottawa, Canada (see Figure 9).

Leveraging results from the stance analysis that was conducted in parallel with the keyness, collocate, and topic modelling analyses, our open-source analyst was able to locate and describe what appeared to be foreign malign information tradecraft. The full analytic flow is depicted in Figure 10.

It is important to note that we did not uncover malicious dissemination of falsified information. However, we did uncover what appeared to be intentional saturation of the information space with a single perspective. Amplifying the volume of a single perspective might convince a population that an issue is more severe and widespread than it is. This foreign malign information campaign (which was possibly led by a single actor or a small team) appeared to begin with identifying a legitimate Western source, then replicating that content and intentionally targeting the Indo-Pacific diaspora in Canada to presumably trigger anxiety or unease in that population.

FIGURE 8
Demoted Search Engine Results

SOURCE: Google search results for the following text: **"Critical Drugs Coalition" fund**.

found to be directed at the Indo-Pacific diaspora in Ottawa, Canada (see Figure 9).
Canada. Information about the characteristics of such efforts and the identification of these specific efforts can be used to identify and tailor responses to foreign messaging, whether these are countermessaging campaigns, media literacy efforts, or other actions that are designed to protect populations from malign information.

It is difficult to know whether the amount of malign information we discovered represents a threat. Because our analysis was limited to known malign websites, and because our analysis of a specific messaging campaign revealed considerable replication across apparently novel (and temporary) websites, it is likely that our analysis has significantly underestimated the size and spread of COVID-19 foreign malign information in the Indo-Pacific.

This was a limited-scope, rapid proof-of-concept study. Future analysis could develop a broader, empirically driven classification algorithm to identify more than the 15 ‘obvious’ sources of foreign malign information used in this study. This classification approach would allow us to find malign information that uses similar linguistic tactics and has a similar topical focus to known malign information websites but that might appear in locations that are not currently known to exist. With a larger data set, such
FIGURE 10
Notional Workflow for Identifying a Malign Information Campaign

work could use unsupervised learning, along with human-driven qualitative analysis, to categorise types of foreign malign information campaigns and strategies. Such an approach would allow us to create categories of malign information that might reflect different strategic objectives or different linguistic tactics and thereby help us understand more about the diversity of foreign malign messaging regarding COVID-19.

**Appendix A. Malign Information Websites**

Malign information articles were identified using a list of URLs from known malign information sources. The URL for each article was parsed to determine whether it originated from any of the websites shown in Table A.1 (i.e., the text of the URL included the entire text of the website).

<table>
<thead>
<tr>
<th>Website</th>
<th>URL</th>
</tr>
</thead>
<tbody>
<tr>
<td>TASS (Russian news agency)</td>
<td><a href="https://tass.com/">https://tass.com/</a></td>
</tr>
<tr>
<td>Russia Insider</td>
<td><a href="https://russia-insider.com/en">https://russia-insider.com/en</a></td>
</tr>
<tr>
<td>RT (formerly Russia Today)</td>
<td><a href="https://www.rt.com/">https://www.rt.com/</a></td>
</tr>
<tr>
<td>Pravda (first online Russian paper)</td>
<td><a href="https://www.pravdareport.com/">https://www.pravdareport.com/</a></td>
</tr>
<tr>
<td>The Moscow Times</td>
<td><a href="https://www.themoscowtimes.com/">https://www.themoscowtimes.com/</a></td>
</tr>
<tr>
<td>SouthFront (Russian world news website)</td>
<td><a href="https://southfront.org/">https://southfront.org/</a></td>
</tr>
<tr>
<td>News Front (Russian news website)</td>
<td><a href="https://en.news-front.info/">https://en.news-front.info/</a></td>
</tr>
<tr>
<td>Fort Russ News (news portal)</td>
<td><a href="https://fort-russ.com/about/">https://fort-russ.com/about/</a></td>
</tr>
<tr>
<td>Katehon (Moscow-based think tank)</td>
<td><a href="https://katehon.com/">https://katehon.com/</a></td>
</tr>
<tr>
<td>Xinhua News Agency (state-run press agency)</td>
<td><a href="http://www.xinhuanet.com/english/">http://www.xinhuanet.com/english/</a></td>
</tr>
<tr>
<td>People’s Daily Online (newspaper owned by the Chinese Communist Party)</td>
<td><a href="http://en.people.cn/">http://en.people.cn/</a></td>
</tr>
<tr>
<td>Global Times (newspaper owned by the Chinese Communist Party)</td>
<td><a href="https://www.globaltimes.cn/">https://www.globaltimes.cn/</a></td>
</tr>
<tr>
<td>Beijing Review (national news magazine)</td>
<td><a href="http://www.bjreview.com/">http://www.bjreview.com/</a></td>
</tr>
<tr>
<td>China Global Television Network</td>
<td><a href="https://america.cgtn.com/">https://america.cgtn.com/</a></td>
</tr>
</tbody>
</table>
Appendix B. Regression Table
As shown in Table B.1, we ran a logistic regression to determine the association between emotions and malign disinformation. We were not predicting classes (i.e., whether there was malign information or not). The malign information articles were identified based on their URLs (see Table A.1 for the list of URLs). There was no test or train step. We ran the regression to determine maximum likelihood estimators for each evaluated emotion using nonduplicate observations without missing data. We were not seeking to develop a model to predict the class of untagged articles.

<table>
<thead>
<tr>
<th>Sentiment Category</th>
<th>Likelihood Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anger score</td>
<td>1.259***</td>
</tr>
<tr>
<td></td>
<td>(0.320)</td>
</tr>
<tr>
<td>Negativity score</td>
<td>0.506***</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
</tr>
<tr>
<td>Positivity score</td>
<td>0.209*</td>
</tr>
<tr>
<td></td>
<td>(0.117)</td>
</tr>
<tr>
<td>Sadness score</td>
<td>0.571</td>
</tr>
<tr>
<td></td>
<td>(0.426)</td>
</tr>
<tr>
<td>Fear score</td>
<td>0.329</td>
</tr>
<tr>
<td></td>
<td>(0.332)</td>
</tr>
<tr>
<td>Constant</td>
<td>–7.087***</td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
</tr>
<tr>
<td>Observations</td>
<td>221,046</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>–2,884.654</td>
</tr>
<tr>
<td>Akaike information criterion</td>
<td>5,781.307</td>
</tr>
</tbody>
</table>

NOTES: * p < 0.1; *** p < 0.001. Standard errors are in parentheses.
Notes

1 See William Marcellino, Krystyna Marcinek, Stephanie Pezard, and Miriam Matthews, Detecting Malign or Subversive Information Efforts over Social Media: Scalable Analytics for Early Warning, Santa Monica, Calif.: RAND Corporation, RR-4192-EUCOM, 2020.

2 As part of the initial exploration of detecting COVID-19 messaging and malign information from foreign sources in the Indo-Pacific, we evaluated several media data sources that could be incorporated into an automated data pipeline. The criteria used in the evaluation of these data sources were organised according to data content, type, and format; availability of historical data; security practices; and cost.

3 Additionally, the NewsAPI data source provider offers an application programming interface capability that directly supports data pipeline automation. This was an integral aspect of the exploration, enabling us to leverage existing in-house capabilities, such as scalable data pipeline infrastructure with RAND’s integrated text mining platform (RAND-Lex), to provide scalable text analysis across these data sources.

4 Our analyses likely represent an undercount of the total malign information because we counted only articles from channels known to propagate malign information in the region. As we discuss in the section, ‘Discovering a Specific Malign Information Campaign’, foreign channels appear to ‘launder’ malign information through a wide variety of web addresses.

5 RAND-Lex’s stance analysis uses an expert dictionary of words and phrases arranged in a taxonomy of 119 language categories (emotions, social relationships, values, temporality, etc.) that was originally developed at Carnegie Mellon University to statistically describe the stance or attitudinal dimension of text collections.

6 The higher taxonomy of RAND’s stance dictionaries has been highly accurate in machine-learning classification and has provided deep insight when used for statistical description. See Jennifer Kavanagh, William Marcellino, Jonathan S. Blake, Shawn Smith, Steven Davenport, and Mahlet G. Tebeka, News in a Digital Age: Comparing the Presentation of News Information over Time and Across Media Platforms, Santa Monica, Calif.: RAND Corporation, RR-2960-RC, 2019; and William Marcellino, Kate Cox, Katerina Galai, Linda Slapakova, Amber Jaycocks, and Ruth Harris, Human-machine detection of online-based malign information, Santa Monica, Calif.: RAND Corporation, RR-A519-1, 2020.

7 To put this into perspective, there are low odds of misinformation (0.002) in the corpus. More than any other emotion we evaluated, anger content is associated with greater increases in these odds. For purposes of scale, holding all other emotions that we evaluated constant, a 1-percentage-point increase in anger is predicted to increase the 0.002 odds to 0.0064 (or roughly 3.5 times).

8 Keyness testing is comparing word frequencies in a text corpus with expected frequencies from a baseline corpus. This shows conspicuously over- or underpresented words to help researchers understand what a corpus is about.

9 Collocate extraction is identifying word pairs or triplets in a text. This shows the strength of association between words, which helps researchers quickly identify abstract concepts, place and person names, and repeated phrases.

10 Topic modelling allows analysts to discover the top-level themes latent within documents.


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About This Report

The Australia Department of Foreign Affairs and Trade (DFAT) provided grant funding to RAND Australia to support a proof-of-concept exploratory study that uses news and blog data to understand efforts by foreign countries to spread malign information regarding coronavirus disease 2019 (COVID-19) in the Indo-Pacific region. Researchers used RAND’s proprietary lexical analysis platform, RAND-Lex, to provide insights on the reach, content, and tactical strategies used in foreign malign information regarding COVID-19 in the Indo-Pacific, building on prior work conducted by RAND researchers examining COVID-19 disinformation. This report is designed for analysts, policymakers, and others who are interested in how foreign countries attempt to shape opinions and attitudes regarding COVID-19.

The research was conducted within the International Security and Defense Policy Center of the RAND National Security Research Division (NSRD). NSRD conducts research and analysis for the Office of the Secretary of Defense, the U.S. Intelligence Community, U.S. State Department, allied foreign governments, and foundations. For more information about RAND Australia, see www.rand.org/australia or contact the RAND Australia director listed on the webpage. Comments or questions specific to this report should be addressed to the project leader, Ryan Brown, at rbrown@rand.org.

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