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**Pandemic Vulnerability Knowledge Visualisation for Strategic Decision-Making: A COVID-19 Index for Government Response in Australia**

**Abstract**

**Purpose:** This study aims to develop a pandemic vulnerability knowledge visualisation index to support the strategic decision-making efforts of authorities.

**Design/methodology/approach:** First, the key vulnerability factors from the literature are identified. Second, using the vulnerability factors as indicators, a composite index is developed. Last, from the index values, a set of vulnerability knowledge maps, showing the vulnerability hotspots, are prepared.

**Findings:** Ten indicators are identified as vulnerability factors that could significantly impact the virus spread risks. Verifying the identified hotspots against the recorded infected cases and deaths has evidenced the usefulness of the index. Determining and visualising the high-vulnerability locations and communities could help in informed strategic decision-making and responses of the authorises to the pandemic.

**Originality/value:** The study demonstrates that the developed pandemic vulnerability knowledge visualisation index is particularly appropriate in the context of Australia. Nonetheless, by replicating the methodologic steps of the study, customised versions can be developed for other country contexts.

**Keywords:** knowledge visualisation; strategic decision-making; community vulnerability; COVID-19; government response; Australia

**Paper type:** Research paper

## 1. Introduction

The outbreak of SARS-CoV-2 emerged in December 2019 from Wuhan, China. In March 2020, the World Health Organisation declared the COVID-19 pandemic. A year after this decleration, the COVID-19 pandemic has reached to an astronomic figure of over 152 million global confirmed cases, and the mortality rate of in excess of 3 million people. Several vaccines has been developed and recently started to be deployed in efforts to control the COVID-19's spread and treat the disease (Paltiel et al., 2021). In addition, to fight the uncontrolled spread of the virus, non-clinical measures have also been introduced as a way to reduce personal contact and transmission including the implementation of social distancing policies, self-isolation, enforced quarantines, movement control orders, travel restrictions, banning of large social gatherings, and mandatory mask wearing (Honey-Roses et al., 2020).

Despite these measures, the local and regional impacts of the COVID-19 pandemic remain greatly heterogeneous (Lone & Ahmad, 2020). Some regions, such as poor metropolitan areas, have witnessed higher infection and mortality rates in contrast to other areas. Subsequently, the local and regional economic impact of the pandemic is variable dependent on an area's location. Additionally, with regards to the fiscal effect, the pandemic has resulted in increased government spending and reduced revenue for all levels of government, which like the general impacts of the disease are non-uniform across all geographic areas.

Given the heterogenous nature of COVID-19 impacts, local governments and municipalities remain on the frontline of crisis management. This is particularly relevant given the potential for repeated peaks in infection rates or in response to future similar crises. To target current and future impacts, precise public health interventions are required including an improved understanding of the most vulnerable people, communities, and geographic locations. In addition, a clear understanding of high-risk or high-vulnerability localities and communities remains critical for authorities to make informed local decisions to help control the spread of the disease. Despite these risks, there is only limited evidence on how to measure and identify vulnerability levels and at-risks socioeconomic groups in our cities and communities (Sparke & Anguelov, 2020).

This brings the critical issue of knowledge management during a pandemic situation (Ammirato et al., 2020). In addition to the knowledge management, knowledge visualisation (Eppler & Platts, 2009) is utmost important for informing authorities in their strategic decision-making (Aas & Alaassar, 2018)—particularly in high public health risk situations such as pandemics, where evidence-base for decision-making is critically important but generally scarce (Lipsitch et al., 2011). In support to this, Araz et al. (2010) emphasised the importance of exercising pandemic preparedness through an interactive simulation and visualisation. To fill this gap, the study aims to develop a pandemic vulnerability knowledge visualisation index to support strategic decision-making efforts of authorities.

## 2. Literature Background

Vulnerability is the moderated capacity of a group or and individual to predict, cope with, resistance and recovery from the force of a natural or human-made hazard such as physical, economic, social, and political

factors, which can terminate the level of vulnerability in people and their capacity to resisting, coping with and recovering from hazards (Morrow, 1999). Vulnerability consists of 'exposure' and 'susceptibility' to harm, and the lack of 'resilience' (Stephenson et al., 2014). As for Diderichsen et al. (2019), exposure is separate to the 'susceptibility' element of vulnerability since it is possible to be exposed, whilst at the same time not susceptible to hazards. Vulnerability also concerns the wider environmental and social conditions that limit people and communities to cope with the impact of hazard (Roncancio & Nardocci, 2016).

Vulnerability factors can be classified in three groups—underlying causes, dynamic pressures, unsafe conditions. Each of these classifications includes the vulnerability factors and the combination of vulnerability and hazard in the case of a disaster. These factors present a starting point for the constructed indices. A vulnerability index is a measurement of the exposure to a hazard. These indices can be an important tool to identify communities where the rate of vulnerability is higher. With reference to disease transmission a vulnerability index can be used to identify limitations with a community that may impact on its ability to mitigate, treat or delay the transmission disease, or to access or utilise measures, which may help decrease the economic and social impacts. While still in the relatively early stages of development there has been some limited efforts in developing vulnerability for the COVID-19 pandemic including: The COVID-19 Community Vulnerability Index (CCVI) (Surgo Foundation, 2020); The Infectious Disease Vulnerability Index (IDVI) (Gilbert et al., 2020); (c) The Indian COVID-19 Vulnerable Regions Index (IVRI) (Acharya & Porwal, 2020); The COVID-19 Social Epidemiological Vulnerability Index (SEVI) (Machariya et al., 2020).

The first study relates to the CCVI, which was developed by the Surgo Foundation (2020) to distinguish vulnerable societies within the context of the pandemic. The index uses a combination of indicators from the Centre's for Disease Control and Prevention's (CDC) Social Vulnerability Index (SVI) (CDC, 2018) and other indices specific to the COVID-19 pandemic (Surgo Foundation, 2020). The SVI is used to measure the expected negative impacts that disasters and disease outbreaks can have on human health and is grouped into four sub-indices: Socioeconomic status; Household composition and disability; Minority status and language; Housing type and transportation. The indicators specific to the COVID-19 pandemic include two additional sub-indices: Epidemiological factors; Healthcare system factors.

The second study utilised the IDVI to evaluate the preparedness and vulnerability against their risk of importing COVID-19. The IDVI consists of seven sub-indices: Socioeconomic vulnerability; Population density; Access to housing and transportation; Epidemiological factors; Health system factors; Fragility; Age (Gilbert et al., 2020).

The third study developed a composite index to evaluate regions and their vulnerability to COVID-19. The index was based on the infrastructural and population characteristics of these regions and included five sub-indices: Socioeconomic factors; Demographic factors; Housing and hygiene factors; Availability of healthcare; Epidemiological factors (Acharya & Porwal, 2020).

The final study developed a combined Social Epidemiological Vulnerability Index (SEVI) to evaluate vulnerability to COVID-19. The index contains four sub-indices: Socioeconomic deprivation factors; Population characteristics; Access to services; Epidemiological factors (Machariya et al., 2020).

Considering the abovementioned indices, various dimension of the vulnerability indices should be argued such as the conflict between susceptibility and vulnerability. In the COVID-19 lexicon, susceptibility is the risk of getting infected by the virus which defines a variety of epidemiological factors. Nonetheless, vulnerability can be determined as risk of infection consequences, such as spreading, morbidity and mortality, and social and economic factors. These indices also included some indicators that are universal, where some of them relevant to the specific country context. Hence, as the spatial, socioeconomic, governance, health systems are not identical across the globe (Ballester-Arnal & Gil-Llario, 2020), it is critical to develop context-driven indices in order to most accurately determine vulnerable communities and locations.

Besides, none of the aforementioned indices contained community emotional or sentiment indicators as a variable in determining the vulnerability levels. The recent research studies and the COVID-19 pandemic have evidenced the importance of community emotions or sentiments (Ammirato et al., 2020) in identifying vulnerabilities that also effect community mental wellbeing (Das & Dutta, 2021). Particularly, social media with its open crowdsourced data provides opportunity for authorities and researchers to capture community perspectives on their vulnerabilities (Kankanamge et al., 2019; Yigitcanlar et al., 2020b; Alomari et al., 2021).

To sum, Australia has responded better than most of developed countries to maintain the society and economy, the consequences of COVID-19 will remain for an extended and would have long-term impacts on the social and economic life (Smith & Judd, 2020). Besides the authorities' interventions, knowledge about past and current pandemic influenzas and compliance with containment measures among Australians are among the main reasons for the successful pandemic damage control (Eastwood et al., 2009; Chang et al., 2020). With this in

mind, and along with the above issues of the need for context-driven indices that consider community emotions or sentiments as an input, this study develops an index for Australia.

## 3. Research Design

### 3.1. Methodology

The methodology for this study followed the prior index development work of Dizdaroglu et al. (2012), Dur & Yigitcanlar (2015) and Yigitcanlar et al. (2020c). The index development work contains three steps. The first step in the methodology was to finalise a list of indicators, which could be used to form the basis of the index. This was done through a literature review, which derived key vulnerability factors that could strengthen or inhibit the ability of the virus to spread throughout the community. Based on this review a total of 10 indicators where identified and used in this study (Table 1). Using these vulnerability factors the second step involved the creation a of composite index—i.e., The COVID-19 Vulnerability Knowledge Visualisation Index (CoVis). Each of the vulnerability factors/indicators used to develop the composite index required an analysis of different datasets to complete the process. The unit of analysis is determined as local government areas (LGAs). A description of indicators, and source of data is shown in Table 1, where an equal weight is considered.

**Table 1.** Indicators CoVis.

| Indicator | Description | Source | Reference |
|---|---|---|---|
| Indicator 1 ($I_1$): Socioeconomic status | Socioeconomic demographics | Australian Bureau of Statistics (ABS) | Khazanchi et al., 2020 |
| Indicator 2 ($I_2$): Disabled people | Quantity of people with physical and/or mental disabilities | ABS | Jalali et al., 2020 |
| Indicator 3 ($I_3$): Senior citizens | Quantity of people above the age of 65 | ABS | Annweiler et al., 2021 |
| Indicator 4 ($I_4$): Public's negative sentiments | Identified people's negative emotional reactions to COVID-19 gathered from twitter sentiment analysis | Queensland University of Technology | Alamoodi et al., 2020 |
| Indicator 5 ($I_5$): Population density | Measurement of population per unit area | ABS | Bhadra et al., 2021 |
| Indicator 6 ($I_6$): International airports | Quantity of international airports | Australian Government | Dollar et al., 2020 |
| Indicator 7 ($I_7$): Cruise ship stops | Quantity of cruises ship stops | Australian Cruise Association | Moriarty et al., 2020 |
| Indicator 8 ($I_8$): Quarantine centres | Quantity of hotel quarantine centres | Official reports | Khraise et al., 2020 |
| Indicator 9 ($I_9$): Infected cases | Quantity of COVID-19 infected cases | State government health departments | Chang et al., 2020 |
| Indicator 10 ($I_{10}$): Hospitals with intensive care units | Quantity of hospitals with COVID-19 intensive care units | Australian Institute of Health and Welfare | Bloomer & Bouchoucha, 2020 |

Once raw values for each of the indicators was obtained from the sources identified in Table 2, they were manually entered into the model and a 'min-max normalisation' calculation applied for the purposes of normalised the data between a scale range of 0 to 1. This process of normalising the raw indicator values was calculated as follows:

$$Inew = \frac{Iraw - Imin}{Imax - Imin}$$ (Eq.1)

Where $I$ corresponds to the indicator value; *new*, *raw*, *min* and *max* subscripts respectively denote normalised (transformed), original, minimum and maximum scores of each indicator.

With the exception of $I_1$ and $I_{10}$, whereby a higher value represents lower vulnerability, all the other indicators increase the risk of COVID-19 relative to the increase of their values. The composite index that was created to analyse the vulnerability of cities and communities was applied to 83 LGAs across Australia by using Microsoft Excel. Lastly, the final and third step was to prepare, from the index values, a set of vulnerability maps, showing the LGA with the highest to lowest risk of vulnerability by using a geographical information system software—ArcGIS Pro. These maps have been displayed in the results section followed by a further discussion of their implications.

In addition to the index calculation, we have also conducted a principal component analysis (PCA), by using IBM SPSS Statistics package, to check the importance levels of the indicators used in the index—to identify the importance levels of indicators that create a considerable impact to the total vulnerability levels.

### 3.2. Case Study

A case study approach was used in this study to assess the vulnerability of communities to the spreading patterns and causes of COVID-19 outbreaks. Australia was select as a case study for a number of reasons. The majority of COVID-19 vulnerability indices completed to date have focused on developing countries. This study provides an opportunity to analyse vulnerability in developed nations and provide an index for assessing this vulnerability. Australia's response to the COVID-19 pandemic has been highlighted for its success relative to other developed nations. The actual impact of the COVID-19 pandemic on Australian cities and regions is quite diverse. This index could shed some light on what factors may have contributed to this diversity. Australia is a large multicultural nation and from both a geographic and socioeconomic perspective contains a diverse range of communities. This makes it a fertile ground for understanding how various characteristics of the community's impact vulnerability to disease outbreak, while ensure other factorsremain relatively stable.

The case study locations were selected amongst the 537 LGAs of Australia (Yigitcanlar, 2006). The primary selection criterion concerned the social media data availability. We obtained geotagged Twitter messages on COVID-19 from Australia (n=96,666), via QUT's Digital Observatory (Yigitcanlar et al., 2020a). Then, a data cleaning process was employed to obtain the mostly relevant tweets for further analysis. To clean the data, the five-step data cleaning process introduced by Arthur et al. (2018) was adopted—time zone filter, date filter, bot filter, relevance filter and text filter (Kankanamge et al., 2020a). As mentioned above, the first two filters—time zone filter and date filter—were adopted at the time of downloading the data through the Twitter API, which tweets other than the given time durations and the tweets circulated related to other countries were removed. The other two filters—bot filter (removal of auto-mated messages), and relevance filter (removal of irrelevant meanings)—were applied later. In total 35,969 tweets remained after cleaning the data. These tweets were found to be originated from 200 LGAs. This data is used to determine the sentiments of populations on the COVID-19 pandemic and its effects on the local communities.

As the literature highlights the importance of sentiments in measuring community vulnerability, a filter was applied to remove LGAs with less than 10 geotagged tweets (Xia et al., 2020; Kankanamge et al., 2020b; Yigitcanlar et al., 2021). This helped data not to be under- or over-estimate the sentiments of the local communities and hence deliver a more reliable and accurate index. This left us with 83 LGAs. The final selection of 83 LGAs included all national, state, and territory capital cities in addition to a diverse range of major city and regional centres, and other remote centres. In selecting a diverse range of population centres, each impacted by various degrees from the COVID-19 pandemic, it was considered an appropriate sample for understanding how various aspects of a community can impact on its vulnerability to disease outbreak.

The data needed for the study is collected between January and May 2020 and the analysis is conducted between June and September 2020. The index provides the vulnerability levels of investigated Australian LGAs as of May 2020.

## 4. Results

### 4.1. Index Results

The Index had indicators specifically designed to evaluate the most important aspects of COVID-19. Accordingly, 83 LGAs analysed in this study was categorised into five clusters based on their risk levels: Higher risk (n=17); High risk (n=16); Moderate risk (n=17); Low risk (n=16); Lower risk (n=17). In total 16 to17 LGAs are assigned to each risk level categories, as our objective was to form as equal as possible clusters.

Higher risk areas (Table 2) includes almost all Australian state and territory capitals including: City of Melbourne (VIC, CoVis: 6.58, Rank #1), City of Sydney (NSW, CoVis: 4.93, Rank #2), Brisbane City Council (QLD, CoVis: 3.7, Rank #4), City of Hobart (TAS, CoVis: 3.35, Rank #6), City of Perth (WA, CoVis: 3.33, Rank #7), City of Darwin (NT, CoVis: 3.02; Rank #9) and ACT (CoVis: 2.4, Rank #14). These results appear to parallel the general spread of the COVID-19 pandemic which in countries such as the USA, China and UK was first identified in major cities before spreading to other parts of the country. Notwithstanding, some higher risk ranking areas such as the City of Hume (VIC, CoVis: 4.08, Rank #3), Cairns Regional Council (QLD, CoVis: 3.5, Rank #5), Whitsunday Regional Council (QLD, CoVis: 3.06, Rank #8), and Gladstone Regional Council (QLD, CoVis: 3.02, Rank #10) were all identified in the top-10 most vulnerable cities, but they are neither capital cities nor located ancillary to capital cities. Nevertheless, common initial observations of these areas include major tourism hubs and major mining and agricultural centres.

**Table 2.** Higher risk areas.

| Rank | LGA | State | $I_1$ | $I_2$ | $I_3$ | $I_4$ | $I_5$ | $I_6$ | $I_7$ | $I_8$ | $I_9$ | $I_{10}$ | CoVis |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | City of Melbourne | VIC | 0.03 | 1.00 | 1.00 | 1.00 | 0.51 | 0.00 | 1.00 | 0.86 | 0.59 | 0.60 | 6.58 |
| 2 | City of Sydney | NSW | 0.70 | 0.02 | 0.06 | 0.42 | 1.00 | 0.00 | 1.00 | 1.00 | 0.14 | 0.60 | 4.93 |
| 3 | City of Hume | VIC | 0.82 | 0.01 | 0.04 | 0.02 | 0.05 | 1.00 | 0.00 | 0.14 | 1.00 | 1.00 | 4.08 |
| 4 | Brisbane City Council | QLD | 0.70 | 0.00 | 0.01 | 0.13 | 0.10 | 1.00 | 1.00 | 0.43 | 0.32 | 0.00 | 3.70 |
| 5 | Cairns Regional Council | QLD | 0.56 | 0.07 | 0.03 | 0.01 | 0.01 | 1.00 | 1.00 | 0.00 | 0.02 | 0.80 | 3.50 |
| 6 | City of Hobart | TAS | 0.02 | 0.07 | 0.07 | 0.02 | 0.08 | 1.00 | 1.00 | 0.29 | 0.01 | 0.80 | 3.35 |
| 7 | City of Perth | WA | 0.68 | 0.07 | 0.08 | 0.15 | 0.26 | 1.00 | 0.00 | 0.29 | 0.01 | 0.80 | 3.33 |
| 8 | Whitsunday Regional Council | QLD | 1.00 | 0.03 | 0.03 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 1.00 | 3.06 |
| 9 | City of Darwin | NT | 0.70 | 0.07 | 0.05 | 0.01 | 0.08 | 0.00 | 1.00 | 0.29 | 0.03 | 0.80 | 3.02 |
| 10 | Gladstone Regional Council | QLD | 0.97 | 0.01 | 0.03 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 1.00 | 3.02 |
| 11 | City of Coffs Harbour | NSW | 0.80 | 0.05 | 0.07 | 0.00 | 0.01 | 1.00 | 0.00 | 0.00 | 0.01 | 0.80 | 2.74 |
| 12 | City of Gold Coast | QLD | 0.43 | 0.09 | 0.04 | 0.03 | 0.05 | 1.00 | 0.00 | 0.14 | 0.14 | 0.80 | 2.72 |
| 13 | Alice Springs Town Council | NT | 0.56 | 0.08 | 0.05 | 0.00 | 0.01 | 1.00 | 0.00 | 0.00 | 0.00 | 0.80 | 2.50 |
| 14 | Canberra | ACT | 0.47 | 0.06 | 0.05 | 0.12 | 0.02 | 1.00 | 0.00 | 0.00 | 0.08 | 0.60 | 2.40 |
| 15 | Mid Coast Council | NSW | 0.64 | 0.17 | 0.55 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 1.00 | 2.40 |
| 16 | Port Macquarie-Hastings Council | NSW | 0.48 | 0.03 | 0.03 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.02 | 0.80 | 2.37 |
| 17 | The City of Greater Geelong | VIC | 0.12 | 0.07 | 0.05 | 0.02 | 0.02 | 0.00 | 1.00 | 0.00 | 0.22 | 0.80 | 2.31 |
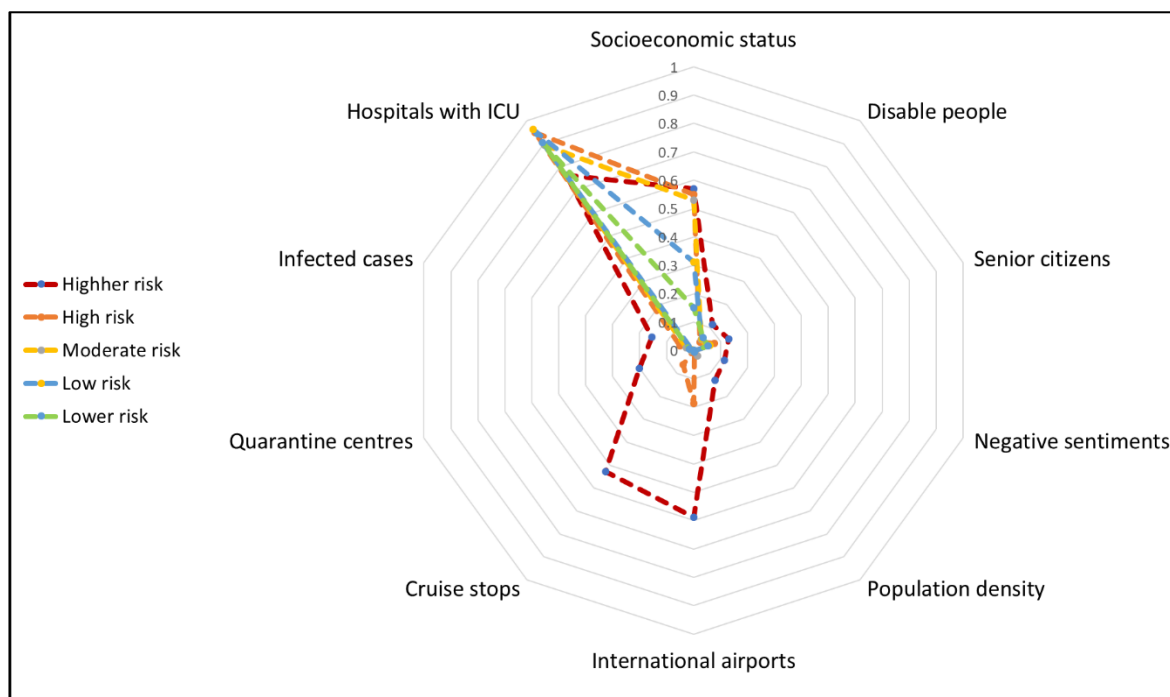


**Figure 1.** Performance of LGAs per CoVis risk categories.

Major risk factors (Figure 1) evident in the top-16 most vulnerable (higher risk) LGAs include: Potential exposure virus outbreak—i.e., distance to airports and cruise stops; Number of hospitals with ICU facilities; Low

social economic status. As of Table 2, the state capitals of this cluster have a higher number of hospitals with ICU facilities, compared to the other LGAs such as Whitsunday Regional Council (QLD), Gladstone Regional Council (QLD), and Mid Coast (NSW) do not have access to hospitals with ICU facilities.

Furthermore, the higher risk cluster includes five LGAs from QLD, four LGAs from NSW, three LGAs from VIC, two LGAs from NT, and one LGA each from WA, ACT and TAS. Interestingly, despite second wave impacts of the virus on VIC, it does not register the highest number of most vulnerable LGAs. Given its ranking as the most vulnerable LGA to COVID-19 outbreak, it is not surprising that the City of Melbourne has the highest number of older residents, disabled people, and the second highest population density of all the 83 LGAs analysed. Besides, it is apparent that these factors could be significant contributors to the increased the risk of COVID-19 outbreak.

The second group of LGAs represents the high-risk areas (Table 3). Out of 16 LGAs belonging to this group, seven are from VIC. They are the Rural City of Mildura (CoVis: 2.28, Rank #18), City of Melton (CoVis:2.21, Rank #20), Shire of Central Goldfields (CoVis: 1.89, Rank #24), Shire of Macedon Ranges (CoVis: 1.89, Rank #25), Surf Coast Shire (CoVis: 1.73, Rank #30), South Gippsland Shire (CoVis: 1.73, Rank #31), and Bass Coast Shire (CoVis:1.7, Rank #32). As a state, VIC has more high risk LGAs compared to the other states. There are four LGAs from QLD, three from NSW, and one LGA from SA and TAS.

**Table 3.** High risk areas.

| Rank | LGA | State | $I_1$ | $I_2$ | $I_3$ | $I_4$ | $I_5$ | $I_6$ | $I_7$ | $I_8$ | $I_9$ | $I_{10}$ | CoVis |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 18 | Rural City of Mildura | VIC | 0.37 | 0.05 | 0.06 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.80 | 2.28 |
| 19 | City of Devonport | TAS | 0.03 | 0.09 | 0.07 | 0.00 | 0.03 | 0.00 | 1.00 | 0.00 | 0.01 | 1.00 | 2.23 |
| 20 | City of Melton | VIC | 0.43 | 0.02 | 0.06 | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 | 0.66 | 1.00 | 2.21 |
| 21 | District Council of Ceduna | SA | 0.47 | 0.09 | 0.59 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 2.15 |
| 22 | Dubbo Regional Council | NSW | 0.03 | 0.01 | 0.03 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 | 1.00 | 2.07 |
| 23 | Shire of Noosa | QLD | 0.94 | 0.02 | 0.02 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 2.01 |
| 24 | Shire of Central Goldfields | VIC | 0.72 | 0.08 | 0.08 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.89 |
| 25 | Shire of Macedon Ranges | VIC | 0.76 | 0.02 | 0.06 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 1.00 | 1.89 |
| 26 | City of Wagga Wagga | NSW | 0.00 | 0.02 | 0.03 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.86 |
| 27 | Queanbeyan-Palerang Regional Council | NSW | 0.76 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.80 |
| 28 | Central Highlands Regional Council | QLD | 0.67 | 0.06 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.77 |
| 29 | Toowoomba Regional Council | QLD | 0.90 | 0.01 | 0.02 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.80 | 1.76 |
| 30 | Surf Coast Shire | VIC | 0.63 | 0.02 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.73 |
| 31 | South Gippsland Shire | VIC | 0.67 | 0.02 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.73 |
| 32 | Bass Coast Shire | VIC | 0.63 | 0.02 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.70 |
| 33 | Bundaberg Regional Council | QLD | 0.06 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.69 | 0.06 |

The major risk factor apparent in this grouping include: Hospitals without adequate ICU facilities; Comparatively a low socioeconomic conditions. Especially, almost all LGAs in this cluster need more hospitals with ICU facilities to face to a sudden surge of a COVID-19 cluster. City of Devonport (TAS), Dubbo Regional Council (NSW), and City of Wagga Wagga (NSW) have a low socioeconomic condition compared to the other LGAs listed in the high-risk group.

The third cluster (Table 4) includes LGAs with moderate risk levels. From the 17 LGAs included in this cluster, six are from VIC, further highlighting the increased vulnerability of VIC. These include the City of Warrnambool (CoVis: 1.64, Rank #35), City of Latrobe (CoVis: 1.64, Rank #36), Colac Otway Shire (CoVis: 1.61, Rank #39), Rural City of Wangaratta (CoVis: 1.61, Rank #40), Shire of Mitchell (CoVis: 1.57, Rank: 43), and Shire Cardinia (CoVis:1.53, Rank #49). A total of three LGAs from NSW are located in this cluster including Tweed Shire (CoVis: 1.61, Rank #41), Central Coast Council (CoVis: 1.56, Rank #44), and Kempsey Shire (CoVis: 1.48, Rank #50). Interestingly this cluster contains four LGAS from SA, including the City of Adelaide (CoVis: 1.69; Rank #34), which is the capital city of South Australia, and the only state or territory capital not located with the 'Higher risk area' or 'High risk area' clusters. Other LGAs from this group were originated from three from QLD, and one from WA. As seen in Figure 1, the main factors that contributed to increased vulnerability within this cluster were: A lower socioeconomic status; The lack of hospitals with ICUs. In addition, the fact that no major airports, cruise stops, or quarantine centres where located within the LGA boundaries of this cluster is likely to explain relatively moderate vulnerability level.

**Table 4.** Moderate risk areas.

| Rank | LGA | State | $I_1$ | $I_2$ | $I_3$ | $I_4$ | $I_5$ | $I_6$ | $I_7$ | $I_8$ | $I_9$ | $I_{10}$ | CoVis |
|------|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|-------|
| 34 | City of Adelaide | SA | 0.04 | 0.06 | 0.06 | 0.18 | 0.00 | 0.00 | 0.14 | 0.01 | 0.80 | 1.69 | 0.04 |
| 35 | The City of Warrnambool | VIC | 0.03 | 0.07 | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.80 | 1.64 | 0.03 |
| 36 | City of Latrobe | VIC | 0.07 | 0.08 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.03 | 0.80 | 1.64 | 0.07 |
| 37 | Western Downs Regional Council | QLD | 0.03 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.64 | 0.03 |
| 38 | City of Victor Harbor | SA | 0.06 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.64 | 0.06 |
| 39 | Colac Otway Shire | VIC | 0.01 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.07 | 1.00 | 1.61 | 0.01 |
| 40 | Rural City of Wangaratta | VIC | 0.02 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.80 | 1.61 | 0.02 |
| 41 | Tweed Shire | NSW | 0.04 | 0.06 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.61 | 0.04 |
| 42 | Sunshine Coast Regional Council | QLD | 0.01 | 0.03 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.06 | 0.80 | 1.59 | 0.01 |
| 43 | Shire of Mitchell | VIC | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.05 | 1.00 | 1.57 | 0.12 |
| 44 | Central Coast Council | NSW | 0.02 | 0.07 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.09 | 0.60 | 1.56 | 0.02 |
| 45 | Shire of Broome | WA | 0.09 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.56 | 0.09 |
| 46 | Fraser Coast Regional Council | QLD | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.55 | 0.02 |
| 47 | City of Port Lincoln | SA | 0.09 | 0.06 | 0.00 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.54 | 0.09 |
| 48 | City of Mount Gambier | SA | 0.09 | 0.07 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.54 | 0.09 |
| 49 | Shire of Cardinia | VIC | 0.32 | 0.05 | 0.04 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.11 | 1.00 | 1.53 |
| 50 | Kempsey Shire | NSW | 0.39 | 0.01 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.48 |

The fourth cluster (Table 5) includes all LGAs with low risk. Out of the 16 LGAs in this cluster, seven were located in regional VIC including the Rural City of Horsham (CoVis: 1.47, Rank #53), Alpine Shire (CoVis: 1.4, Rank #57), Shire of Northern Grampians (CoVis: 1.38, Rank #60), Shire of Moira (CoVis: 1.37, Rank #61), Shire of Mount Alexander (CoVis: 1.35, Rank #62), Shire of Hepburn (CoVis: 1.34, Rank #64), and the Rural City of Benalla (CoVis: 1.32, Rank #66). An additional three were from NSW and QLD, and one from NT, SA and WA. All councils located in this cluster would be considered a rural or remote. The primary factors associated with decreased vulnerability appear to be: Not having enough hospitals with adequate ICU facilities; Relatively poorer socioeconomic conditions.

**Table 5.** Low risk areas.

| Rank | LGA | State | $I_1$ | $I_2$ | $I_3$ | $I_4$ | $I_5$ | $I_6$ | $I_7$ | $I_8$ | $I_9$ | $I_{10}$ | CoVis |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 51 | Byron Shire | NSW | 0.40 | 0.02 | 0.03 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.48 |
| 52 | Port Pirie Region | ACT | 0.35 | 0.05 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.47 |
| 53 | Rural City of Horsham | VIC | 0.37 | 0.02 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.46 |
| 54 | City of Townsville | QLD | 0.49 | 0.06 | 0.05 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.02 | 0.80 | 1.43 |
| 55 | City of Kalgoorlie-Boulder | WA | 0.32 | 0.03 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.42 |
| 56 | Rockhampton Regional Council | QLD | 0.51 | 0.04 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.41 |
| 57 | Alpine Shire | VIC | 0.30 | 0.04 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.40 |
| 58 | Katherine Town Council | NT | 0.28 | 0.06 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.40 |
| 59 | Winecarribee Shire | NSW | 0.27 | 0.03 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 1.00 | 1.40 |
| 60 | Shire of Northern Grampians | VIC | 0.29 | 0.03 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.38 |
| 61 | Shire of Moira | VIC | 0.24 | 0.05 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.37 |
| 62 | Shire of Mount Alexander | VIC | 0.24 | 0.03 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.35 |
| 63 | Somerset Regional Council | QLD | 0.28 | 0.03 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.35 |
| 64 | Shire of Hepburn | VIC | 0.12 | 0.12 | 0.10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.34 |
| 65 | Bathurst Regional Council | NSW | 0.32 | 0.14 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.33 |
| 66 | Rural City of Benalla | VIC | 0.20 | 0.05 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.32 |

The fifth cluster (Table 6) represents the LGAs with the lowest risk. Out of the 17 LGAs in this cluster, five LGAs are from VIC, four from NSW, three from WA, three from QLD, two from TAS, and one each from SA, QLD, and NT. Most of the LGAs from the lowest risk cluster have a high socioeconomic index, and a low population density. Similar to the low risk LGA cluster, none of the LGAs from the lowest risk LGA cluster are exposed to: Quarantine centres; International airports; Cruise stops. These reasons have directly caused to reduce the risk level of the LGAs with the lowest vulnerability.

**Table 6.** Lower risk areas.

| Rank | LGA | State | $I_1$ | $I_2$ | $I_3$ | $I_4$ | $I_5$ | $I_6$ | $I_7$ | $I_8$ | $I_9$ | $I_{10}$ | CoVis |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 67 | Mackay Regional Council | QLD | 0.48 | 0.01 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.32 |
| 68 | MacDonnell Regional Council | NT | 0.20 | 0.06 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.31 |
| 69 | City of Greater Shepparton | VIC | 0.40 | 0.02 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.80 | 1.28 |
| 70 | City of Maitland | NSW | 0.19 | 0.01 | 0.02 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.02 | 1.00 | 1.28 |
| 71 | Shire of Collie | WA | 0.10 | 0.14 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.26 |

| 72 | Shire of Augusta-Margaret River | WA | 0.12 | 0.07 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.26 |
| 73 | City of Port Augusta | SA | 0.10 | 0.08 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.25 |
| 74 | Huon Valley Council | TAS | 0.07 | 0.09 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.23 |
| 75 | City of Ballarat | VIC | 0.24 | 0.02 | 0.07 | 0.01 | 0.02 | 0.00 | 0.00 | 0.00 | 0.04 | 0.80 | 1.19 |
| 76 | City of Busselton | WA | 0.03 | 0.09 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.17 |
| 77 | City of Lithgow | NSW | 0.05 | 0.03 | 0.08 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.16 |
| 78 | City of Wodonga | VIC | 0.27 | 0.02 | 0.04 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.80 | 1.15 |
| 79 | Goulburn Mulwaree Council | NSW | 0.03 | 0.03 | 0.08 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 1.00 | 1.14 |
| 80 | City of Launceston | TAS | 0.11 | 0.09 | 0.07 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.09 |
| 81 | City of Greater Bendigo | VIC | 0.07 | 0.06 | 0.07 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 0.80 | 1.07 |
| 82 | City of Wollongong | NSW | 0.03 | 0.06 | 0.07 | 0.01 | 0.04 | 0.00 | 0.00 | 0.00 | 0.04 | 0.80 | 1.05 |
| 83 | Shire of Wellington | VIC | 0.08 | 0.08 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.80 | 1.05 |

In addition to the index calculation, the study also evaluated the fit of the used 10 indicators of CoVis, through a correlation analysis (Table 7) and PCA. The results showed a statistically significant correlation among several variables. An important relation is the very high correlation of disabled people indicator with senior citizens (correlation 0.819, sig.<0.001) and negative sentiments (0.839, sig.<0.001). In addition, co-existence of population density (indicator 5) and quarantine centres (indicator 8) is very high (correlation 0.922, sig.<0.001) indicating that these indices are likely to emerge together. An interesting result is that hospitals with ICU facilities indicator is negatively correlated with all the other indicators. However, the correlations are (all the cases except one) relatively low (below 0.4) but they are statistically significant on 99% level indicating the absence of the other indicators when adequate ICU hospital facilities are present. In terms of PCA, the Bartlett test of sphericity is statistically significant (sig. <0.001) with an approx. Chi-Square of 622.629 (df: 45, Sig: .000) indicating that the preconditions for such an analysis are good. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy is also over 0.6 (0.71). The analysis indicates that communalities and eigenvalues of three main components of the rotated matrix explain cumulatively 79.1% of the total variance. Single communalities are, however, relatively low and straightforward intuitive naming of the components is difficult. It is however clear that elements of: Socioeconomic condition and seniority; Urban characteristics; Hospital conditions are identifiable in the PCA matrices.

**Table 7:** Correlation matrix of indices.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1. Socioeconomic status | 1.000 | -.251 | -.129 | -.074 | .057 | .054 | .086 | .045 | .084 | -.163 |
| 2. Disabled people | -.251 | 1.000 | .819 | .839 | .371 | -.052 | .281 | .514 | .329 | -.156 |
| 3. Senior citizens | -.129 | .819 | 1.000 | .694 | .313 | -.095 | .181 | .423 | .280 | -.085 |
| 4. Negative sentiments | -.074 | .839 | .694 | 1.000 | .747 | .038 | .421 | .837 | .424 | -.398 |
| 5. Population density | .057 | .371 | .313 | .747 | 1.000 | .038 | .439 | .922 | .275 | -.371 |
| 6. International airports | .054 | -.052 | -.095 | .038 | .038 | 1.000 | .146 | .152 | .217 | -.394 |
| 7. Cruise ship stops | .086 | .281 | .181 | .421 | .439 | .146 | 1.000 | .569 | .205 | -.372 |
| 8. Quarantine centers | .045 | .514 | .423 | .837 | .922 | .152 | .569 | 1.000 | .397 | -.509 |
| 9. Infected cases | .084 | .329 | .280 | .424 | .275 | .217 | .205 | .397 | 1.000 | -.213 |
| 10. Hospitals with ICUs | -.163 | -.156 | -.085 | -.398 | -.371 | -.394 | -.372 | -.509 | -.213 | 1.000 |

### 4.2. Spatial Analysis Results

The index results are spatially analysed by employing a geographical information software—ArcGIS Pro. The spatial analysis provided a clearer image of the spatial distribution from higher risk LGAs to the lower risk

LGAs. Accordingly, all state and territory capitals, except for Adelaide and Canberra, were in the higher risk cluster. Additionally, a number of areas outside state capital cities were in higher areas cluster; in fact, four of the top-10 ranking LGAs were from Greater Capital City Statistical Areas (GCCSA).

GCCSAs are designed to represent a socioeconomic characterisation of each of the eight state and territory capital cities. This refers to the greater capital city boundary includes people who regularly socialise, shop, or work within the city, but live in the small towns and rural areas adjacent to the city. It does not define the built-up edge of the city. Accordingly, the GCCSAs act as a functional boundary, which represent the capital city-based community movements. As the COVID-19 literature repeatedly highlighted the risk of spreading COVID-19 virus become high when the movements of the community become high. Mostly, when one area become a virus hotspot the COVID-19 risk of adjacent areas become relatively high.

For instance, Xie et al.'s (2020) study findings proved that there was an increment of relative COVID-19 risk in adjacent provincial boundaries in China around the COVID-19 hotspot identified. Likewise, this fact was repeatedly evidenced by using the case studies across the world, such as Brazil (Fortaleza et al., 2020) and Germany (Kuebart & Stabler, 2020). Accordingly, spatial analysis at the GCCSA become an ideal parameter as it represents both social and spatial boundaries of community movements in Australian states/territories (Yigitcanlar et al., 2020c).

In related to the state of Victoria, five LGAs used for this study are located within the GCCSA. From them, two are in the higher risk cluster—City of Melbourne, and City of Hume. Three of the LGAs located at the edge of the GCCSA of Melbourne are in high risk (City of Melton), moderate risks (Shire of Mitchell), and low risk (Shire of Cardinia). Nevertheless, as COVID-19 spreads fast with high community interactions, the adjacent and in between LGAs around City of Melbourne and City of Hume are also at a higher risk. This places the following neighbouring LGAs potentially under risk due to easy access, City of Hobsons Bay, City of Maribyrnong, City of Moonee Valley, City of Yarra, City of Port Phillip, and City of Stonnington is at a higher risk (Figure 3). Hence, the COVID-19 related studies repeatedly proved that travel restrictions could reduce the impact/spread of COVID-19 (Chinazzi et al., 2020).

Only two LGAs were analysed within the greater capital city area (GCCA) of Sydney. Accordingly, Sydney LGA is at a higher risk. Central Coast Council located at the boundary of the GCCSA is at a moderate risk level. As of the spatial location of Sydney and the Central Coast Council, the people from the adjacent LGAs of Woollahra, Waverley, Randwick, Botany Bay, Inner West, Canada Bay, Hunters Hill, Lane Cove, North Sydney, and Mosman are at a high risk. Figure 2 visualises the risk levels of LGAs based on the CoVis scores. Especially, as in Figures 2 and 3, most of the aforesaid LGAs are small in extent and high in population, which could be a key factor to increase the spread of COVID-19 risk. Canberra, the national capital located in ACT, acts as a separate LGA, although it locates within the state boundary of NSW. As per the CoVis, ACT is a high-risk area and most importantly the adjacent LGA of Queanbeyan-Palerang Regional Area is also at the high-risk cluster. Hence, the nearby LGAs such as Yass Valley, Eurobodalla, and Snowy Monaro Regional can be identified as the potential risk areas.

Within the GCCSAs of Brisbane, two LGAs were analysed. From them Brisbane is a higher risk area and the Somerset Regional Council is at low risk. Accordingly, the LGAs of Ipswich, Logan, and Moreton Bay can be identified as potential high-risk zones. Nonetheless, the area of these LGAs are big in size with a low population density compared to the LGAs located within the GCCAs of Sydney. This geographic factor could reduce the spread of COVID-19 to a certain extent if appropriate measurements are taken in a timely manner. Most significantly, and as an excellent spatial example, Perth is the only LGA analysed and presented as a higher risk area within the boundary of GCCSA of Perth. Accordingly, LGAs of Subiaco, Vincent, South Perth, Victoria Park, Nedlands, and Bayswater were identified as potential high-risk areas. By applying whatever the regulations imposed to control COVID-19 for potential risk areas could lead to reduce the impact of COVID-19. Similarly, Darwin is the only LGA analysed and identified as a high-risk area as per the CoVis. Nonetheless, the adjacent LGA's population density is comparatively low compared to the other LGAs with high risk. Thus, there is a very low potential to spread COVID-19 out of the premises of Darwin. Adelaide is in the low risk areas. Hence, there is a very low potential of increasing the risk of the nearby LGAs.
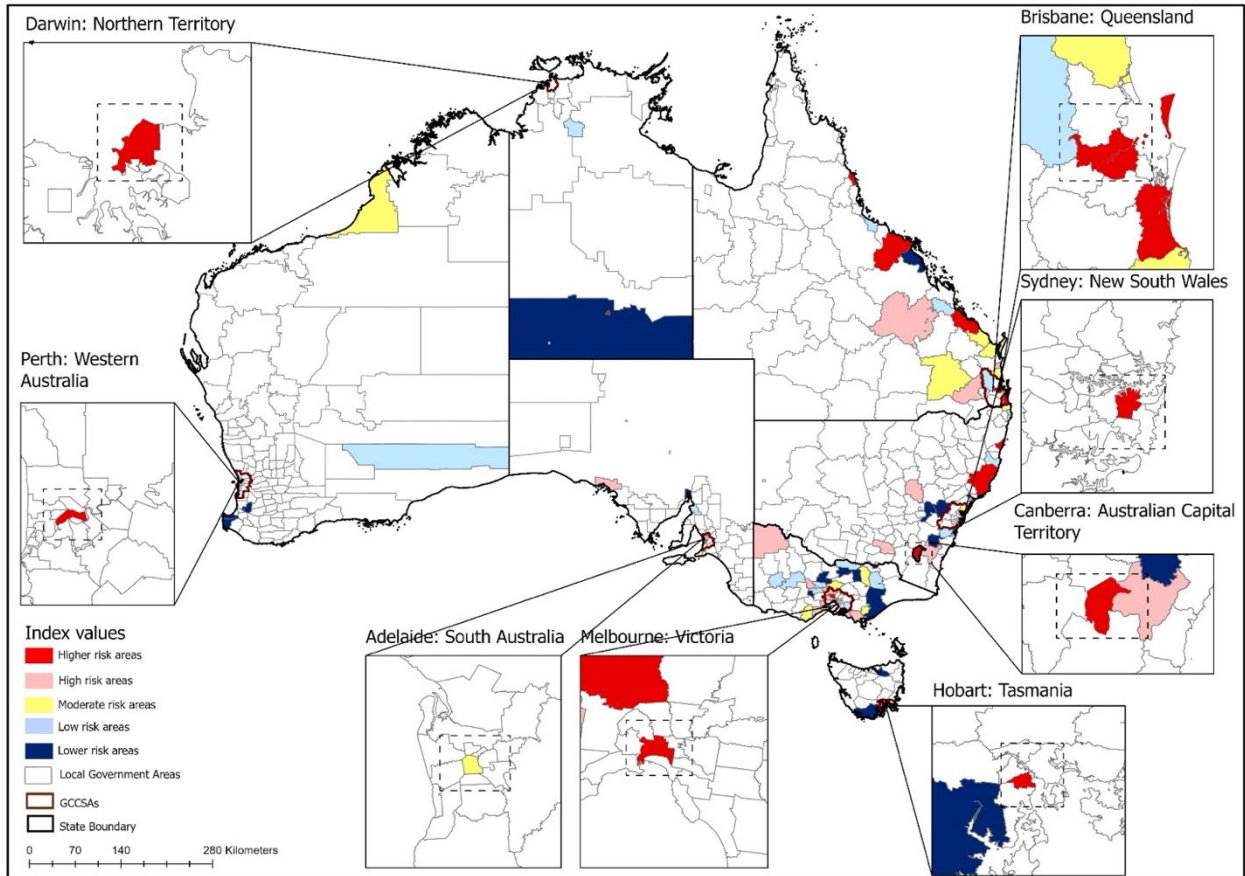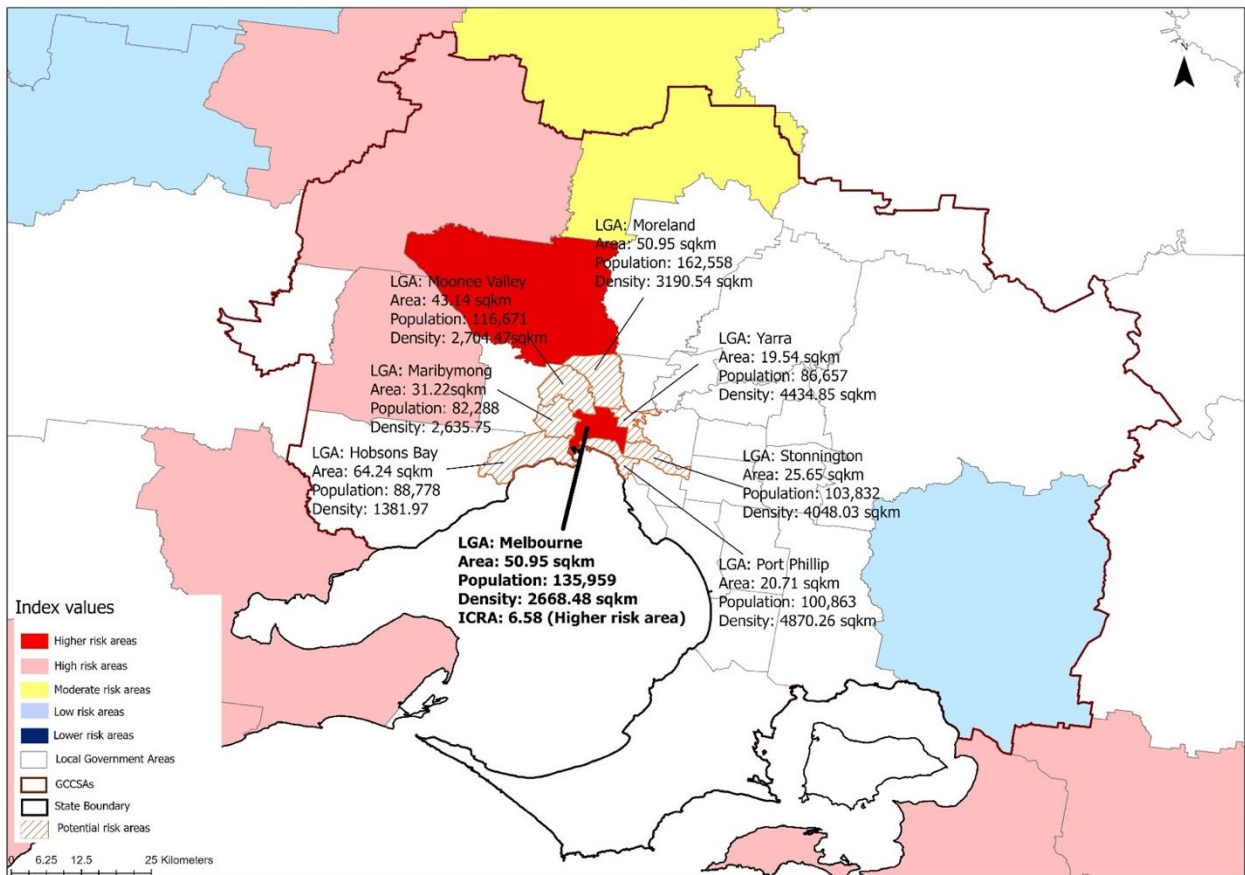
**Figure 2**. Risk areas as per CoVis.



**Figure 3**. An example of identifying risk areas as per CoVis.

## 5. Discussion

### 5.1. Index Development

This study has identified a total of 10 indicators, derived from the literature, considered to significantly impact on the vulnerability of local communities against the spread of the SARS-CoV2 virus and subsequent disease COVID-19. Given the rapid spread of the virus and increasing cases of COVID-19 seen throughout the world the CoVis presents a significant opportunity for researchers and decision-makers to evaluate the vulnerability of communities to new outbreaks of SARS-CoV2 and other transmittable viruses. Like previous studies on COVID-19 it incorporates both socioeconomic, epidemiological, and healthcare system factors as potential contributors to community vulnerability and highlights the importance of understanding factors which contribute to both community susceptibility such as disability, age, socioeconomic status, population density, and number of recorded cases, in addition to factors contributing to community resilience such as number of hospitals with ICU units (Gilbert et al., 2020).

In addition to the aforementioned factors that consider both susceptibility and resilience as a contributor to vulnerability, this study contributes to existing research by building on existing indices and considering the role that infrastructure such as international airports, cruise terminals, and quarantine centres, and community sentiment plays in increasing susceptibility and resilience to virus. For instance, infrastructure such as airports and terminals provide access points by which viruses can enter the community. Without proper resilience measures in place at these access points there is a risk of rapid transmission throughout the community and surrounding areas (Gostic et al., 2020). This aligns with evidence from Australia which saw some of the largest outbreaks of the virus linked to cruise terminals where appropriate resilience measures, including traveller screening, was either not yet in place, had been overlooked, or was unable to detect infected travellers (Zhou et al., 2021). Around the same time, early interventions such as health screening at international airports and mandatory quarantine likely limited the potential reach of the virus, particularly in the early stages of its transmission. Similarly, failures in hotel quarantine including lack of appropriate measures to ensure quarantine employees were complying with directions was linked to the second COVID-19 outbreak in Victoria and further highlight the risks associated with accessibility to quarantine facilities (Mao, 2020).

Regarding community sentiment a number of studies have highlighted the importance of mental health and psychological wellbeing, with regards to both its potential physical impact on members of the community, and also its potential to affect decision-making and the ability, or desire, to comply with existing control measures (Baldwin et al., 2020). The higher risk areas identified in this study showed significantly higher levels of negative sentiment during the COVID-19. In fact, the City of Melbourne which was identified the most at risk LGA in Australia also scored the highest for negative sentiment. While negative sentiment, particularly in Melbourne, is unlikely to be the cause of the initial outbreaks, long-term lockdown measures and poor messaging may have led to increased negative sentiment and mental health issues (Zhou et al., 2021), potentially resulting in increased complacency, impaired decision-making or unwillingness to comply with government resilience measures—such as lockdowns and social distancing. This is could have been a significant factor which following the second outbreak in the state caused the virus to quickly infiltrate, and flourish within the community.

The addition of infrastructure and community sentiment into the index is an important because it helps to contributes to an index that better balances the social, environmental, geographical and healthcare factors that contribute to social vulnerability. Furthermore, the introduction of sentiment into the model creates added value in the role of that people's emotional behaviour can play in the spread of disease. This is particularly important consideration given that human behaviour is not static and can be influenced by a range of different factors. Ensuring this balance is important as social vulnerability indexes are often criticised for lacking consideration of social and spatial factors and for having only a static understanding of human and environmental interactions (Rufat et al., 2019).

### 5.2. Spatial Analysis

Spatial analysis has used across the world to identify the geographic characteristics of those infected by COVID-19 (Franch-Pardo et al., 2020), to identify the relationship among spatial, temporal and epidemiological characteristics, to predict the global spread of COVID-19 based on geographic and climatic characteristics (De Angel Solá et al, 2020), and to conduct local level COVID-19 risk assessments. According to Xie et al. (2020), all the adjacent areas of Wuhan (China) were categorised into the severely affected areas cluster, which the community interaction was high across the above areas. Therefore, higher the social interactions across different geographic boundaries higher the possibility of virus spread. Consequently, most of countries enforced travel restrictions considering geographic boundaries as a COVID-19 control measure.

For instance, this study only analysed Sydney LGA within the GCCA of NSW state and it is the second highest LGA from the higher risk cluster (CoVis: 5.27). Additionally, this study identified all the other adjacent

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areas such as Canada Bay, Inner West, Randwick, Rockdale, and Woolhara are as potential high-risk areas. The number of confirmed COVID-19 cases reported in the above areas—i.e., Canada Bay (n=40), Inner West (n=87), Randwick (n=106), Waverly (n=204), Woolhara (n=102) and Bayside (n=77), further validate the findings of the CoVis based risk area identification process.

### 5.3. Decision-Making

Our experience during the COVID-19 pandemic has shown, one more time, that knowledge is the most precious resource we have (Millar & Choi, 2010), and sound knowledge management approaches are extremely critical to take appropriate actions to stop the spreading of the virus, save lives, and address the socioeconomic challenges caused by the pandemic and keep the essential services and amenities running (Deliu, 2020; Wang & Wu, 2020). Along with this knowledge visualisation is also deemed to be a critical tool for the communication of the gathered information between decision-makers and also the public (Van-Biljon & Osei-Bryson, 2020)—as after all it is knowledge visualisation is key enabler for strategic decision-making.

Knowledge visualisation via indices help decision-makers to be proactive by identifying risk areas at the earliest and to be prepared. The pandemic has created negative externalities for almost all aspects of our lives. Consequently, identifying the potential risk and being proactive about it will reduce these current or potential/forthcoming externalities/disruptions. In 2018, the top-three highest gross domestic product growth in Australian cities were originated from Melbourne, Canberra, and Brisbane. These state capitals provide employment opportunities, where community movements are very high. The CoVis help decision-makers to identify weaker areas to develop relevant policies and actions to tackle them. Most importantly, the higher risk area clusters, which includes most of the state and territory capitals, are located closer to international airports. This increase the exposure to the virus. Therefore, authorities need to consider developing consolidated policies to control arrival of the contaminated passengers and the spread of the virus to GCCAs and regional areas.

Further, with the exception of Hume (QLD) other than the state capitals, the higher and high-risk areas appear to be located away from state capital in either tourist, or industry, agriculture and mining centres. These are regional cities with relatively limited health facilities to respond to a vicious virus spread. This emphasises the need of government intervention to stop spreading COVID-19 virus to high risk regional areas. Additionally, regional LGAs with large tourist populations—i.e., Cairns (QLD), City of Gold Coast (QLD), Alice Springs (NT)—need strong policy measures to be protect themselves in the case of an outbreak. Therefore, it is important to understand the risk levels not only in state and territory capitals, but also in other regional areas. This will help the authorities to face any sudden surge of COVID-19 clusters with strong policies, until vaccines deployed globally.

Further, the statistical analysis, i.e., PCA, identified the significance of socioeconomic status ($I_1$), disabled people ($I_2$) and senior citizens ($I_3$) in altering the COVID-19 vulnerability, over the number of quarantine centres ($I_8$) and number of hospitals with ICU units ($I_{10}$). This provides insights for the decision-makers about which areas to invest in managing COVID-19 situations more effectively. For instance, people with underlying non-communicable diseases—e.g., diabetes, cardiovascular disease, chronic respiratory disease and cancer—have a high risk for developing severe and even fatal COVID-19 (Reshadat et al., 2019; Khademi et al., 2021). Mostly, senior citizens and disabled people may have such diseases along with possible low immunity systems. Therefore, authorities should launch adequate intervention programmes to take care of the health of such group of people during the pandemics.

In sum, knowledge visualisation through the CoVis provides more informed, effective and efficient decisions for authorities, policymakers and healthcare decision-makers to act upon. Along with this study, rapidly growing literature on the topic, such as Almeida et al. (2020) and Currie et al. (2020) for instance, demonstrate how knowledge visualisation tools can help reduce the impact of COVID-19. Especially by harnessing the power of visualisation in knowledge management to help understand the complexity of pandemics and provide informed decisions, policies and actions for tackling them (Eppler & Burkhard, 2007). The index introduced in this study should not be only taken at face value. The key contribution of knowledge visualisation through the developed index for decision-makers goes beyond bringing evidence-base to the decision process, it can also create a transparent and participatory decision co-creation opportunity (Kim et al., 2005).

## 6. Conclusion

Making cities and citizens prepared for a fight with a deadly virus is strategic and requires innovative and critical thinking. Unexpectedly, the COVID-19 pandemic appeared and caused massive disruption across the world. The entire world is looking forward to a new normal to restart the jeopardised lifestyles. Although 'lockdown' was the prime strategy adopted in most of the countries to face this pandemic, it is not practical at a long run as it stops the urban economic and social engines from working. To tackle the ongoing pandemic tragedy, policymakers need to make sure that the basic city functions move as usual while ensuring the safety

and the health of the citizens. Thus, identifying high risk areas at the earliest and making an area prepared for a sudden surge of a COVID-19 cluster is highly critical, which this study attempted to.

Considering the above, this study emphasised the need for a novel and balance vulnerability index to predetermine the high-risk areas and prepare local communities and risk groups to face the pandemic situation. Different than other vulnerability indices, CoVis proposed in this study also considers human emotions, which is undoubtedly important for developing actions to better tackle the pandemic effects. Overall, CoVis is unique and important due to three main reasons: Use of main risk factors specially increase the fatality risk due to COVID-19; Consideration of main transmission points; Considered community emotions that reflect the mental fitness of the citizens.

The index developed in this study best suits for a situation where the virus effects are not active. Hence, more alterations could be done to use this index for contract tracing once the virus is active in an area. It will help to expedite testing procedures too. Lastly, the knowledge created from this indexing exercise for Australia could be also useful to make local authorities better prepared to a pandemic situation elsewhere.

## Acknowledgements

## References

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