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A scoping review of COVID-19 research adopting quantitative geographical methods in geography, urban studies, and planning: a text mining approach

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ABSTRACT

Quantitative geographical methods have played an important role in COVID-19 research. To complement and extend previous review studies, we conduct a scoping review of COVID-19 studies employing quantitative geographical approaches by focusing on 331 papers published in 45 journals in geography, urban studies, and planning. We identify four major research themes (clusters): (1) how SARS-CoV-2 viruses spread in cities, (2) the COVID-19 mortality (death) rates and their association with socioeconomic variables, (3) how the COVID-19 pandemic changed people's mobilities, and (4) how the COVID-19 pandemic affects air pollution. We conclude that spatial models play a key role in COVID-19 quantitative geographical approaches, and human mobility is an important and widely studied topic. We also reveal a lack of research focusing on environmental pollution (other than air pollution) that potentially worsened during the pandemic.

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COVID-19; GIS; quantitative; scoping review; text mining

1. Introduction

Since December 2019, the COVID-19 pandemic has been a major global public health concern. Researchers from diverse disciplines have been tirelessly developing ways to mitigate the social, environmental, and economic impacts of the pandemic. Quantitative geographical methods have played an important role in COVID-19 research (Boulos and Geraghty 2020; Kim and Kwan 2021a; Smith and Mennis 2020; Yang et al. 2020). Utilizing numeric data with locational properties, these methods include spatial and spatiotemporal modelling, visualization, optimization, simulation, and other statistical methods (McLafferty 2020; McLafferty, Guhlincozzi, and Winata 2021; Murray 2010).

For instance, COVID-19 dashboards have proved effective in sharing pandemic-specific geospatial information (i.e. maps, statistics on confirmed case and death rates, and charts) with citizens (e.g. Dong, Du, and Gardner 2020; Kolak et al. 2021; Kumar et al. 2021). COVID-19 pandemic spatial and spatiotemporal models have been actively developed by researchers (e.g. Cuadros et al. 2020; Liu and Li 2021; Nasiri et al. 2021; Oyedotun and Moonsammy 2021; Rohleder and Bozorgmehr 2021). These models focus on how the SARS-CoV-2 virus spreads and ultimately predict the severity of the pandemic based on metrics such as

daily confirmed cases and death rates. These models are particularly helpful in developing evidence-based pandemic policies (e.g. lockdown and quarantine) that aim to mitigate the pandemic's impacts.

Previous studies have reviewed the role of quantitative geographical approaches in COVID-19 research. For example, Franch-Pardo et al. (2020) reviewed 63 studies that were conducted in the very early stage of the pandemic (January – April 2020). Their review highlights the importance of geospatial data and GIScience methods in COVID-19 research and illustrates five research areas: spatiotemporal analysis, health and social geography, environmental variables, data mining, and web-based mapping. Franch-Pardo et al. (2021) extended their earlier review by focusing on papers published in the second half of 2020 and yielded similar findings. Similarly, Fatima et al. (2021) identified four quantitative geographical methods by reviewing 38 papers published before September 2020. They found that clustering, hotspot analysis, space-time scan statistics, and regression modelling were utilized frequently. McLafferty et al. (2021) discussed quantitative geographical approaches in COVID-19 research from critical perspectives. They recommended that researchers and policymakers be cautious about uncertainties and biases in COVID-19 data.

To complement and extend previous review studies, we conduct a scoping review of COVID-19 studies employing quantitative geographical approaches. Specifically, our study aims to (i) include more recently published papers and (ii) identify major research themes. First, our scoping review expands the study timeline by including papers published in 2021 to provide a more comprehensive review. Extending the study timeline of the scoping review is important because of the continuing nature of the COVID-19 pandemic, with many COVID-19 research papers forthcoming that previous reviews have not covered.

Second, we identify major research themes to enhance our understanding of the role of quantitative geographical approaches in COVID-19 research. Since the pandemic has impacted almost all aspects of our lives, including social, environmental, and economic aspects, examining the pandemic's impacts has been an important research topic for geographers (Laituri et al. 2021). This examination reveals gaps and under-studied areas of the pandemic. By implementing a text mining method, we identify major research themes from a much larger collection of COVID-19 papers adopting quantitative geographical approaches.

2. Data and methods

2.1. Data

We focused on 331 COVID-19 research papers that adopt quantitative geographical approaches in 45 peer-reviewed academic journals, specifically in the fields of geography, urban studies, and planning (Table 1). We created a list of these journals by referring to multiple sources, including a research article (e.g. Franklin et al. 2021) and the Scimago Journal Rank (SJR)'s 'Geography, Planning, and Development' and 'Urban Studies' categories (SJR

2021). As there is no singular list of journals that adopt quantitative geographical approaches, we assessed whether each journal was suitable for our research purpose based on the journal's aim and scope statements. These 45 journals can represent the general research trends in geography, urban studies, and planning.¹

We manually searched each journal for COVID-19 papers adopting quantitative geographical approaches by using keywords such as *COVID* and *COVID-19*. From our search query, we checked if the paper was an empirical study (i.e. we excluded review and commentary papers) and utilized quantitative geographical methods by referring to its data and method sections. We defined quantitative geographical methods broadly by including a wide spectrum of quantitative methods, such as spatial and spatiotemporal modelling and visualization, optimization, simulation, and other statistical methods (McLafferty 2020; McLafferty, Guhlincozzi, and Winata 2021; Murray 2010). Three of the authors cross-validated the selection results to minimize errors. The search was conducted in late October 2021, indicating that our analysis is based on papers published between January 2020 and October 2021.

2.2. Methods: clustering abstracts of COVID-19 research papers adopting quantitative geographical approaches

To identify major research themes of COVID-19 studies adopting quantitative geographical approaches, we utilized the text mining method (Bafna, Pramod, and Vaidya 2016; Green et al. 2020), which is one of the machine learning methods (Figure 1). This method yields several clusters to which papers that share a similar research theme are assigned. We used each paper's abstract for the text mining. We did not consider papers' titles and keywords because abstracts

Table 1. 45 peer-reviewed academic journals (331 papers) that typically publish papers adopting quantitative geographical approaches. The number of selected papers published in each journal is in parentheses.

Number of Papers	Journals
10+	<i>Sustainable Cities and Society</i> (46), <i>ISPRS International Journal of Geo-Information</i> (44), <i>Health and Place</i> (27), <i>Cities</i> (25), <i>SSM Population Health</i> (25), <i>Spatial and Spatio-temporal Epidemiology</i> (15), <i>GeoJournal</i> (12), <i>Journal of Regional Science</i> (12), <i>Applied Geography</i> (11)
5–9	<i>Transactions in GIS</i> (8), <i>Landscape and Urban Planning</i> (7), <i>Regional Studies</i> , <i>Regional Science</i> (7), <i>Annals of the American Association of Geographers</i> (6), <i>International Journal of Health Geographics</i> (6), <i>International Journal of Urban Sciences</i> (6), <i>Frontiers in Built Environment</i> (5), <i>Journal of Urban Health</i> (5), <i>Journal of Urban Management</i> (5), <i>Professional Geographers</i> (5)
3–4	<i>Annals of GIS</i> (3), <i>Geocarto International</i> (3), <i>Geographical Review</i> (3), <i>Geo-spatial Information Science</i> (3), <i>International Journal of Digital Earth</i> (3), <i>International Journal of Geographical Information Science</i> (3), <i>Journal of Geographical Sciences</i> (3), <i>Papers in Applied Geography</i> (3), <i>Population, Space and Place</i> (3), <i>Urban Studies</i> (3)
1–2	<i>Applied Spatial Analysis and Policy</i> (2), <i>Cartography and Geographic Information Science</i> (2), <i>Computers, Environment and Urban Systems</i> (2), <i>Environment and Planning B</i> (2), <i>Geographical Research</i> (2), <i>Journal of American Planning Association</i> (2), <i>Journal of Geographical Systems</i> (2), <i>The Annals of Regional Science</i> (2), <i>Computational Urban Science</i> (1), <i>European Urban and Regional Studies</i> (1), <i>Geographical Analysis</i> (1), <i>Habitat International</i> (1), <i>International Journal of E-Planning Research</i> (1), <i>Journal of Maps</i> (1), <i>Nature Sustainability</i> (1), <i>Papers in Regional Science</i> (1)

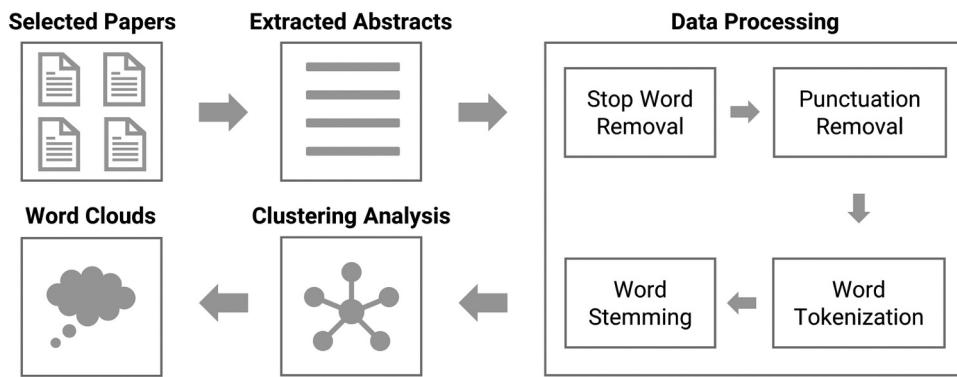


Figure 1. Overview of our research method (text mining).

typically reflect important information obtained from the title and keywords.

The first step is data processing, which includes addressing stop words, stemming words, and calculating a term frequency-inverse document frequency ($tf \cdot idf$) matrix. We removed stop words (e.g. 'a', 'the', 'of', 'this') that are less meaningful for clustering papers from the abstracts of the papers in our database. Note that the stop words also included several variations of the word 'COVID-19' (e.g. 'COVID', 'COVID-19', 'Corona'). Removing stop words from abstracts allows clustering to be done based on more meaningful information from each abstract, which is important to increase the quality of text mining. After removing stop words from the abstract of each paper, we stemmed each word to change it to the root form (e.g. removing '-s', '-ed', '-ing').

In the next step, we calculated a *tf-idf* matrix. This matrix has 331 rows (i.e. 331 abstracts in our database) and 3,871 columns. The number of columns indicates the number of unique stemmed words (not including stop words) in the abstracts of all 331 papers. Each entity in the matrix indicates a *tf-idf* value of a word t in an abstract d (Equation 1).

$$tf-idf(t, d) = tf(t, d) \times \log \frac{n}{1 + df(t)} \quad (1)$$

where $tf(t, d)$ indicates the term frequency of a word t in an abstract d , n denotes the number of abstracts in our database (i.e. 331), and $df(t)$ denotes the number of abstracts that contain a word t . For clustering papers, using $tf-idf$ is better than using simple word frequency because $tf-idf$ considers the unique contribution of each word to the entire abstract, which leads to a better quality of clustering (Bafna, Pramod, and Vaidya 2016). Words that appeared

more times in a paper tend to have a higher *tf-idf* index value than words appeared less times in the paper. However, words appeared in more papers tend to have a lower index value than words appeared in fewer papers.

The third step is clustering papers by using the *tf-idf* matrix created in the second step (Bafna, Pramod, and Vaidya 2016; Kim and Gil 2019; Singh, Tiwari, and Garg 2011). We selected the K-means++ clustering algorithm (a variation of the K-means clustering algorithm) because we can control seed values, allowing us to have consistent clustering results. We used the default setting of the K-means++ clustering algorithm in Python’s scikit-learn library (Pedregosa et al. 2011). We used Euclidean distance to calculate the similarity score between two abstracts by referring to the *tf-idf* matrix. To select the number of clusters (N_c), we observed three clustering performance evaluation metrics: the elbow method, the Davies-Bouldin score (DBS score), and the silhouette score (Han, Pei, and Kamber 2011). Regarding the elbow method and the DBS score, the number of clusters is determined when the score’s drop rate becomes lower. For the silhouette score, a higher score indicates a better cluster quality. Additionally, we qualitatively observed the clustering results to see if they provided meaningful and significant interpretations. As a result, each abstract was assigned to one of the N_c clusters. For abstracts assigned to each cluster, we also summarized the number of abstracts in terms of the papers’ study area (geographic region). By developing an ad-hoc Python programme utilizing several packages (e.g. Bird, Klein, and Loper 2009), we also created word clouds that visualize important words that compose each cluster. These word clouds are particularly

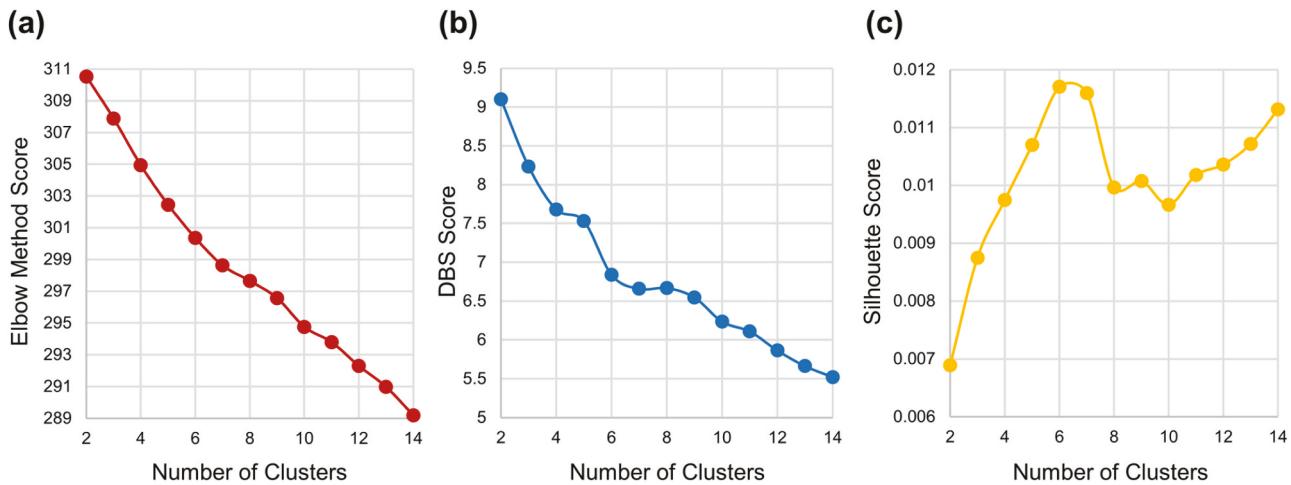


Figure 2. Clustering evaluation metric results based on the (a) elbow method, (b) DBS score, and (c) silhouette score. (Note: Regarding the elbow method and the DBS score, the number of clusters is determined when the score's drop rate becomes lower. For the silhouette score, a higher score indicates a better cluster quality. Additionally, we qualitatively observed the clustering results to see if they provided meaningful interpretations.).

useful for identifying and visualizing a research theme of each cluster.

3. Results

We first present the results of clustering evaluation metrics to decide the number of clusters. Figure 2 illustrates the results of the clustering evaluation metrics. Figure 2(a) is based on the elbow method, Figure 2(b) is based on the DBS score, and Figure 2(c) is based on the silhouette score. (Refer to Section 2.2 regarding how these scores were used for determining the cluster numbers.) Overall, the clustering evaluation metrics indicate that possible cluster numbers are four (2[b]), six (2[b] and 2[c]), and seven (2[a], 2[b], and 2[c]). It is worth mentioning that both quantitative (i.e. metric-based) and qualitative (i.e. interpretation by researchers) evaluations are used when determining the number of clusters (e.g. Han, Pei, and Kamber 2011; Witten, Frank, and Hall 2011).

We decided on four clusters because the primary clustering results of six and seven clusters did not provide interpretable and significant research themes for their clusters. In other words, since four clusters provide the clearest interpretable results, we decided to base our analysis using four clusters: Cluster #1 (122 papers, 36.9%), Cluster #2 (77 papers, 23.3%), Cluster #3 (111 papers, 33.5%), and Cluster #4 (21 papers, 6.6%). Figure 3 illustrates a word cloud for each cluster. The

following subsections discuss each cluster in detail and identify the major research themes of each cluster.

3.1. Cluster #1: papers that investigated how SARS-CoV-2 viruses spread in cities by using spatial models

Cluster #1 consists of 122 papers (36.9% of 331 papers total). Figure 3(a) illustrates a word cloud representing the important words that compose this cluster, where the larger size of a word indicates a more important word that uniquely contributes to the cluster. The word cloud illustrates these important words: *Cities, Case, Population, Spatial, Urban, Infection, Spread, Transmission, and Model*.

We identified the major research theme of Cluster #1 as *Papers that investigated how SARS-CoV-2 viruses spread in cities by using spatial models*. Since the beginning of the COVID-19 pandemic, we have witnessed that various spatial models – such as hot spot analysis (e.g. Das et al. 2021; Huang 2021; Kuznetsov and Sadovskaya 2021; Purwanto et al. 2021), space-time scan statistics and clustering (e.g. Desjardins, Hohl, and Delmelle 2020; Hohl et al. 2020; Liu et al. 2021; Pribadi et al. 2021; Wang et al. 2020; Zheng, Wang, and Li 2021) – play an important role in modelling the transmission of viruses in order to better understand the pandemic. Moreover, researchers have paid special attention to cities and urban areas (e.g.

(a) Cluster #1 (122 Papers)



Important words: Cities, Case, Population, Spatial, Urban, Infection, Spread, Transmission, and Model

(b) Cluster #2 (77 Papers)



Important words: Death, Rate, Mortality, Health, Region, Association, Spatial, and Economy

(c) Cluster #3 (111 Papers)



Important words: Mobility, Activity, Change, Travel, Lockdown, Social, People, Different, and Patterns

(d) Cluster #4 (21 Papers)



Important words: Air, Pollution, PM_x , Lockdown, Quality, Concentration, NO_x , Cities, Reduction, SO_x , Decrease, and CO

Figure 3. Word cloud result of (a) cluster #1 (papers that investigated how SARS-CoV-2 viruses spread in cities by using spatial models), (b) cluster #2 (papers that investigated the COVID-19 mortality rates and their association with socioeconomic variables by using spatial models), (c) cluster #3 (papers that investigated how people's mobilities (activity-travel patterns) have been changed by the COVID-19 pandemic), and (d) cluster #4 (papers that investigated how the COVID-19 pandemic affects air pollution).

Ghosh et al. 2020; Gupta, Biswas, and Kabiraj 2021; Huang et al. 2022; Kawlra and Sakamoto 2021; Liu 2020; Panda and Ray 2021), which are major epicentres of the COVID-19 pandemic. In Cluster #1, China (40 papers, 33.3%) and the U.S. (18 papers, 15.0%) are the most-studied geographic areas of these papers, accounting for approximately 50% of the papers in the cluster.

3.2. Cluster #2: papers that investigated the COVID-19 mortality rates and their association with socioeconomic variables by using spatial models

Cluster #2 consists of 77 papers (23.3% of 331 papers total). The word cloud ([Figure 3\(b\)](#)) highlights several important words: *Death, Rate, Mortality, Health, Region, Association, Spatial, and Economy*. We identified one major and one sub-theme.

The major research theme of this cluster (57 of 77 papers, 74.0%) is: *Papers that investigated the COVID-19 mortality rates and their association with socioeconomic variables by using spatial models*. We also observe several common words (e.g. 'Spatial', 'Case', 'Rate') that appear in both Clusters #1 and #2, indicating that the major research theme of Cluster #2 is similar to that of Cluster #1. However, papers in Cluster #2 particularly focus on mortality (death) rates as a variable to be investigated, which is different from confirmed cases. The regional pattern of COVID-19 death rates and how these death rates are associated with social and economic conditions are essential research themes in COVID-19 studies that adopt quantitative geographical approaches (e.g. Cassan and Van Steenvoort 2021; Friedman and Lee 2021; Grekousis, Wang, and Liu 2021; Hamidi, Ewing, and Sabouri 2020; Harris 2020; Kim et al. 2021; Riley et al. 2021; Vanthomme et al. 2021; Yang, Kim, and Matthews 2021). This is because these studies' results can provide important insights into existing socio-spatial disparities in health policy and infrastructure that may lead to disparities in COVID-19 death rates.

We also identified one sub-theme within this cluster (20 papers). These papers investigate the impacts of the COVID-19 pandemic on people's health outcomes, particularly focusing on mental health and well-being (e.g. Alnasrallah and Alshehab 2020; Chen, Zou, and Gao 2021; Finucane et al. 2022; Long et al. 2021; Vloo et al. 2021; Yang and Xiang 2021). In Cluster #2, papers focusing on the U.S. are the most common (32 papers, 42.1%), followed by papers focusing on multiple countries that often include middle- and high-income group countries (15 papers, 19.7%). One interesting observation is that there is a lower percentage of papers focusing on China in Cluster #2 (2.6%) than in Cluster #1 (3.3%).

3.3. Cluster #3: papers that investigated how people's mobilities (activity-travel patterns) have been changed by the COVID-19 pandemic

There are 111 papers in the third cluster (33.5% of 331 papers total). We identified one major and two sub-themes (Figure 3(c)). The word cloud's important words are: *Mobility, Activity, Change, Travel, Lockdown, Social, People, Different, and Patterns*.

The major research theme of this cluster (50 of 111 papers, 45%) is: *Papers that investigated how people's mobilities (activity-travel patterns) have been changed by the COVID-19 pandemic*. Understanding people's mobility is one of the key research themes in studies adopting quantitative geographical approaches (Kwan and Schwanen 2016), and this is also the

case for COVID-19 research. By utilizing human mobility and activity-travel data, researchers have investigated how the COVID-19 pandemic (especially lockdown policies) affects people's mobility or activity-travel patterns (e.g. Huang et al. 2022; Kar, Le, and Miller 2021; Long and Ren 2022; McKenzie and Adams 2020; Trasberg and Cheshire 2021).

We also identified two sub-themes within this cluster. The first sub-theme (33 of 111 papers, 29.8%) is the impact of human mobility on the COVID-19 pandemic, such as virus transmission, new cases, and mortality rates (e.g. Abulibdeh and Mansour 2022; Chiba 2021; Guo et al. 2021; Kosfeld et al. 2021; Manout and Ciari 2021; Praharaj and Han 2022). The second sub-theme (28 of 111 papers, 25.2%) includes research on other human mobility topics, such as the pandemic's impacts on people's physical activities (e.g. Mitra et al. 2020; Nigg et al. 2021; Portegijs et al. 2021; Sadeghipour et al. 2021; Shaer et al. 2021).

Regarding the study area, the U.S. is the most studied area (29 papers, 26.6%), followed by multi-country regions (7 papers, 6.4%), China (7 papers, 6.4%), Japan (6 papers, 5.5%), Spain (6 papers, 5.5%), and the U.K. (6 papers, 5.5%). These six study areas account for approximately 56% of the papers in this cluster.

3.4. Cluster #4: papers that investigated how the COVID-19 pandemic affects air pollution

Cluster #4 consists of 21 papers (6.6% of 331 papers total). We identified one major research theme by observing the word cloud (Figure 3(d)) and the papers assigned to this cluster. The word cloud illustrates several important words: *Air, Pollution, PM_x, Lockdown, Quality, Concentration, NO_x, Cities, Reduction, SO_x, Decrease, and CO*. Many papers in this cluster investigated the impacts of the pandemic on air pollution concentration levels – such as PM_x, NO_x, SO_x, and CO – in cities (e.g. Basu et al. 2021; Han, Zhao, and Gu 2021; He, Pan, and Tanaka 2020; Polednik 2021; Tang et al. 2021; Tao et al. 2021; Xin et al. 2021). Regarding the study area, the highest number of studies (8 papers, 38.1%) focused on multiple countries (e.g. Bar et al. 2021; Benchrif et al. 2021; Sharma and Verma 2021; Wang and Li 2021), followed by 6 papers (28.6%) focused on India (e.g. Behera et al. 2021; Kumar et al. 2020; Roy and Balling 2021; Sathe et al. 2021). Compared to the previous three clusters, this is an interesting observation that may imply that air pollution is one of the most important environmental issues in India.

4. Discussion

4.1. Discussion on clustering results

To understand the role of quantitative geographical approaches in COVID-19 research, we applied a text mining method to 331 papers' abstracts and identified four clusters related to major research themes. We discovered a number of important findings by observing these clustering results.

First, spatial methods and models (e.g. hot spot analysis, space-time scan statistics, and spatial clustering) play a key role in COVID-19 quantitative geographical approaches, which aligns with findings from previous reviews (e.g. Fatima et al. 2021; Franch-Pardo et al. 2020; Franch-Pardo et al. 2021). Clusters #1 and #2 account for approximately 60% of the 331 papers, and many papers in these two clusters utilize various spatial models. For instance, hot spot analysis was employed to detect hot spots of new COVID-19 cases (e.g. Das et al. 2021; Huang et al. 2021). The space-time scan statistics method was utilized to detect statistically significant COVID-19 spatio-temporal clusters (e.g. Desjardins, Hohl, and Delmelle 2020; Hohl et al. 2020). Overall, these quantitative geographical methods are crucial for producing geographic knowledge pertaining to understanding the pandemic and formulating public health policies (e.g. identifying where to prioritize in providing public resources to mitigate the negative impacts of the pandemic).

Second, in terms of research topics, human mobility is an important and widely studied topic in COVID-19 research (Cluster #3), which aligns with our general expectations. Understanding human mobility has been one of the core research themes in studies adopting quantitative geographical approaches (Kwan and Schwanen 2016). Thus, it is reasonable to observe many studies on human mobilities.

Additionally, it is interesting to observe more studies focusing on air pollution rather than other environmental pollutants (Cluster #4). Considering the wide spectrum of potential environmental impacts (e.g. water, waste, etc.) of the COVID-19 pandemic (e.g. Benson, Bassey, and Palanisami 2021; Burlea-Schiopou et al. 2021; Elsaid et al. 2021; Haghnazari et al. 2022; Lokhandwala and Gautam 2020; Peng et al. 2021; Sarkodie and Owusu 2021; Yunus, Masago, and Hijioka 2020), our results revealed a lack of research effort on environmental pollutions that potentially have been worsened by the pandemic, such as solid medical wastes, including large quantities of disposed face masks (Sangkham 2020).

Moreover, we found that data availability plays an important role in shaping research theme clusters. For

example, many researchers were able to conduct studies on the spatial modelling of COVID-19 cases (Cluster #1) and death rates (Cluster #2) because data were available from public health authorities such as the World Health Organization (WHO) and the U.S. Centers for Disease Control and Prevention (CDC). Also, many public data dashboards – such as *Our World in Data*, *The New York Times*, and *Johns Hopkins University COVID-19 Dashboard* – provided detailed COVID-19 data (e.g. daily confirmed cases and death rates). By utilizing publicly available COVID-19 data, researchers were able to establish spatial models to understand the COVID-19 pandemic, which led to many research papers (i.e. Clusters #1 and #2).

Cluster #3 adds another piece of evidence in support of the importance of data availability. During the COVID-19 pandemic, various mobility datasets have been made available to researchers, such as Google Mobility Report and Apple Mobility Report (e.g. Hamidi and Zandiatashbar 2021; Marcén and Morales 2021; Oliveira et al. 2021; Saha, Mondal, and Chouhan 2021). These mobility datasets are derived from millions of users' mobile phone signal locations. Other mobility datasets include smart card data, cell phone location signal data, and geo-tagged SNS data (e.g. Bhin and Son 2021; Caicedo, Walker, and González 2021; Eom, Jang, and Ji 2022; Jiang, Huang, and Li 2021). Due to recent advances in high-performance computing resources, large mobility datasets can be processed quickly. This has resulted in many COVID-19 studies on human mobility (i.e. Cluster #3). Cluster #4 also provides evidence of the importance of data availability. We illustrated that air pollution gained more attention than other environmental pollutants (e.g. water and waste). One possible explanation is that air pollution datasets are more readily available than other environmental pollutants. Global air pollution datasets, which are high resolution spatially and temporally, are easily available to researchers due to recent advances in remote sensing. However, this is not the case for other environmental pollutants whose datasets are relatively difficult to obtain.

4.2. Future research directions

Based on the clustering results, we identify five potential future directions for COVID-19 research adopting quantitative geographical approaches.

First, although many studies have already focused on spatial modelling (e.g. Clusters #1 and #2), we recommend that researchers keep focusing on this topic because of the persisting situation of the COVID-19 pandemic at the time of writing. The COVID-19 pandemic has had several phases regarding new confirmed cases

and death rates, and these phases differ geographically. Moreover, people's behavioural reactions to the pandemic have changed over time, such as quarantine fatigue and change in people's COVID-19 risk perceptions (e.g. Kim and Kwan 2021b; Wise et al. 2020). Therefore, more comprehensive research on the COVID-19 pandemic through spatial modelling is still needed to enhance our understanding of the pandemic.

However, as Helbich et al. (2021) argued, COVID-19 research on spatial modelling needs to address spatio-temporal uncertainties and scale issues to mitigate potential methodological issues. These include the modifiable areal unit problem (MAUP; Openshaw 1984), the modifiable temporal unit problem (MTUP; Cheng, Adepeju, and Preis 2014), the uncertain geographic context problem (UGCoP; Kwan 2012), and the neighbourhood effect averaging problem (NEAP; Kwan 2018), which have been extensively studied in the context of quantitative geographical approaches but not necessarily in the COVID-19 research (e.g. Huang and Kwan 2022). This is one of the important future research directions in quantitative geographical approaches, which will eventually improve models to promote public health emergency preparedness and response.

Second, we recommend that researchers focus on emerging topics such as disparities in vaccination site accessibility and vaccination rates. Although vaccination is one of the most important topics related to the COVID-19 pandemic, our clustering analysis results at the time of writing revealed that it was less studied, with some exceptions (e.g. Alemdar et al. 2021; Yang, Kim, and Matthews 2021; Nino, Hearne, and Cai 2021). Some studies have investigated the important role of telehealth that helps healthcare accessibility (e.g. COVID-19 vaccination clinics) during the pandemic (e.g. Alford-Teaster et al. 2021; Yang, Kim, and Matthews 2021). One possible explanation is that our analysis was based on papers published before October 2021, when fewer people were vaccinated. Thus, we recommend that future researchers investigate important topics related to vaccination, such as disparities in vaccination site accessibility, geographic patterns of vaccine hesitancy, and so on.

Third, regarding Cluster #3, we recommend that researchers focus on other aspects of human mobility in COVID-19 research. As we discussed, many previous studies utilized mobility data obtained from mobile phone signal locations while focusing on travel distance as a key human mobility variable. Due to the nature of mobility data obtained from mobile phone signal locations, many studies did not investigate other important dimensions of human mobility, such as travel mode choice and travel purpose. Moreover, there could be

potential uncertainties and biases related to mobile phone signal locations (Kwan 2016; Mooney and Pejaver 2018). Thus, we recommend that future studies overcome these limitations by diversifying data sources (e.g. household travel surveys) to properly measure multifaceted aspects of human mobility.

Fourth, we recommend that researchers investigate a wider spectrum of environmental factors in addition to air pollution. It is widely known that the COVID-19 pandemic has affected almost all aspects of our environment (Laituri et al. 2021). For example, there might be huge impacts on water, soil, and waste because of an exponential increase in personal protective equipment (e.g. disposable face masks) usage around the world (e.g. Elsaid et al. 2021; Peng et al. 2021; Sarkodie and Owusu 2021). Understanding these environmental impacts geographically could be an important future research topic in COVID-19 research with quantitative geographical approaches.

Lastly, we recommend that researchers pay more attention to low- and middle-income countries (LMICs). Our clustering results indicate that only a few papers in our selected journals studied LMICs. Studies in LMICs might be restricted because of limited available data and research resources. However, it is important to investigate the COVID-19 pandemic and its impacts on people living in those countries because the pandemic can exacerbate and widen the existing global inequality in economic and health outcomes (e.g. Kim et al. 2022; Laituri et al. 2021). Thus, humanitarian research efforts are needed to fill this critical gap.

4.3. Limitations

Our scoping review study has several limitations that future studies may address. One of these limitations is that our review focused only on papers published in journals of geography, urban studies, and planning. Quantitative geographical methods appear in other interdisciplinary journals (e.g. those in the public health field). Additionally, our review excluded non-English journals. By excluding these journals, our review might have omitted some study areas (e.g. those where most researchers do not publish results in English), research topics, and roles of quantitative geographical approaches in COVID-19 research. Furthermore, future studies can consider adopting more advanced text mining methods, such as Latent Dirichlet Allocation (Blei et al. 2003) and BERT (Devlin et al. 2018), in order to provide a more nuanced understanding of clusters and their meanings and implications in COVID-19 research (Huang et al. 2022). Moreover, we manually determined whether a paper was related to quantitative

geographical approaches or not. There could have been human errors in our decisions, although we endeavoured to minimize any errors by cross-validation. Lastly, future review studies can focus on the role of various data types, models (e.g. spatial regression, geographically weighted regression, spatio-temporal models), and scales in COVID-19 studies adopting quantitative geographical approaches, which is an important methodological topic (Helbich, Browning, and Kwan 2021).

5. Conclusion

This study provided a scoping review of COVID-19 papers that adopt quantitative geographical approaches by focusing on 331 papers published in 45 journals in geography, urban studies, and planning. We identified four major research themes (clusters) of the 331 papers by applying a text mining method to the papers' abstracts. The first cluster consists of papers investigating how SARS-CoV-2 viruses spread in cities using spatial models. The second cluster consists of papers examining the COVID-19 mortality (death) rates and their association with socioeconomic variables using spatial models. The third cluster consists of papers studying how the COVID-19 pandemic has changed people's mobilities (activity-travel patterns). Finally, the fourth cluster consists of papers investigating how the COVID-19 pandemic affects air pollution. We also identified gaps in existing COVID-19 research adopting quantitative geographical approaches and discussed future research directions. Overall, our study highlights the important roles of quantitative geographical approaches in COVID-19 research, identifies research gaps, and recommends future research directions that aim at mitigating the pandemic as well as its negative impacts.

Note

1. It is worth mentioning that our journal selection approach cannot capture research papers that adopt quantitative geographical approaches but appear in other interdisciplinary journals. We did not include journals that focus on specific themes because our research goal is to investigate the role of quantitative geographical approaches in the overall fields of geography, urban studies, and planning. However, it should be noted that we included health and medical geography journals, as they published a significant portion of COVID-19 research.

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Disclaimer statement

The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of any agency of the U.S. government. Assumptions made within the analysis are not a reflection of the position of any U.S. government entity.

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