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Human mobility and COVID-19 transmission: a systematic review and future directions

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ABSTRACT

Without a widely distributed vaccine, controlling human mobility has been identified and promoted as the primary strategy to mitigate the transmission of COVID-19. Many studies have reported the relationship between human mobility and COVID-19 transmission by utilizing the spatial-temporal information of mobility data from various sources. To better understand the role of human mobility in the pandemic, we conducted a systematic review of articles that measure the relationship between human mobility and COVID-19 in terms of their data sources, mathematical models, and key findings. Following the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement, we selected 47 articles from the Web of Science Core Collection up to September 2020. Restricting human mobility reduced the transmission of COVID-19, although the effectiveness and stringency of policy implementation vary temporally and spatially across different stages of the pandemic. We call for prompt and sustainable measures to control the pandemic. We also recommend researchers 1) to enhance multi-disciplinary collaboration; 2) to adjust the implementation and stringency of mobility-control policies in corresponding to the rapid change of the pandemic; 3) to improve mathematical models used in analysing, simulating, and predicting the transmission of the disease; and 4) to enrich the source of mobility data to ensure data accuracy and suitability.

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Human mobility; COVID-19 transmission; systematic review; mobility data; mathematical modelling

1. Introduction

Human mobility plays an important role in the transmission of infectious diseases. With the increase of human mobility caused by the development of transportation networks and globalization, the spread of infectious diseases can be unprecedentedly rapid and difficult to prevent and control, resulting in pandemics. Such pandemics have been witnessed in history, for example, the 1918 novel influenza A (H1N1) pandemic, the 2009 H1N1 pandemic, and the current coronavirus disease 2019 (COVID-19). Without a widely distributed vaccine, controlling human mobility has been identified and promoted as the primary strategy to mitigate the transmission of COVID-19 (Gatto et al. 2020; Kucharski et al. 2020; S. Wang, Liu, & Hu, 2020; Yabe et al. 2020). During this

pandemic, various policies have been implemented worldwide to restrict human mobility across and within countries, including international travel bans, national border closures, restrictions between states and cities, stay-at-home orders, limited private and public gatherings, as well as closing schools, universities, workplaces, and public transportation (Hale and Webster 2020).

Since the outbreak, academic researchers have put substantial efforts into studying the association between human mobility and COVID-19 transmission, applying various datasets and mathematical models in different countries and regions. While many studies have reported the efficacy of mobility restrictions on controlling the spread of the novel coronavirus (Kraemer et al. 2020a; Kucharski et al. 2020; Wang et al., 2020; Yabe et al.

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2020), the timeline and stringency of social restriction policies and lockdown orders have been vociferously challenged due to significant social and economic costs (Bonaccorsi et al. 2020; Lecocq et al. 2020). Additionally, many studies applied simulation and prediction models to forecast the potential spread of the novel coronavirus based on various policies interventions (Prem et al. 2020; Wu, Leung, and Leung 2020). Therefore, there is an urgent need to summarize and compare the findings of these publications to support stakeholders to adopt the most effective mobility measures to control the spread of the novel coronavirus domestically and internationally.

In this systematic review, we summarized the results of the association between human mobility and COVID-19 transmission in terms of study purposes, data usage, modelling approaches, and key findings. Based on the findings, we suggested research directions in the spatial and temporal dimensions for future studies. Through collective efforts from multiple disciplines, we hope to mitigate the spread of COVID-19 with evidence-based solutions and support stakeholders to be better prepared for future public health emergencies given the increased globalization, suburbanization, and interruption of human beings to eco-systems.

2. Method

We followed the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement to select articles and to report the findings. PRISMA statement is a guideline developed to support researchers to conduct systematic reviews (Moher et al. 2009). We applied the checklist of PRISMA with the items to report in a systematic review and a flow diagram indicating the workflow of selecting articles in a systemic review (Moher et al. 2009). We commenced with searching through the Web of Science (WoS) Core Collection of all the published articles between January 2020 to September 2020 to cover the most recent publications with the topic of human mobility and COVID-19. WoS is the most widely used and authoritative database of research publications and citations. WoS Core Collection Coverage includes more than 20,900 journals plus books and conference proceedings from various disciplines (Birkle et al. 2020). The searching terms we used are '(((COVID-19 OR "novel coronaviruses" OR 2019-nCov OR SARS CoV-2) AND ("human mobility" OR "human movement" OR "population flow" OR "social distanc*" OR "physical distanc*" OR "travel restriction" OR "movement control" OR "stay-at-home" OR "lockdown" OR "shelter-in-place"))'.

The flow diagram of the article selection through different phases of the review was presented in Figure 1. We limited our search to published and early access articles, resulting in a total number of 1,649 articles. We then excluded the articles in irrelevant areas (e.g. psychology, neuroscience, neurology, and surgery), narrowing down 868 articles. We further excluded 755 articles that do not meet our inclusion criteria (Table 1) by screening their titles and abstracts. Through reading and assessing full texts, 47 articles highly relevant to our review's interest were finally selected. We summarized and analysed the information of the study countries/regions, study purposes, data resources, modelling approaches, and key findings. This information was also presented in Supplementary Table 1. Based on what we found, we proposed future research directions of mobility-transmission studies.

3. Results

3.1 Data sources and features

The selected papers mainly rely on two types of data: COVID-19 data at different scales and human mobility data. COVID-19 data in terms of the number of confirmed and susceptible cases, deaths, and recovered cases are usually easy to retrieve from research institutes, public health authorities, or government reports, while human mobility data are multi-sourced with specific applications. This review mainly focuses on human mobility data regarding its sources, public accessibility, spatial and time coverage, update frequency, advantages, and disadvantages (Table 2).

The first type of mobility data is big data gathered by technology companies, including Baidu, SafeGraph, Google, and Tencent. For example, Google mobility data is created by aggregated and anonymized data sets from users who have turned on the *Location History* setting in the products such as Google Maps (Aktay et al. 2020). It is encoded as a percentage change in the mobility metric compared to the baseline of human mobility from January 3 to 6 February 2020 (Aktay et al. 2020). Unlike Google mobility data, SafeGraph mobility data adds unique and valuable insights into the mobility change by estimating the aggregated and anonymized summary of foot traffic to 6 million points-of-interest in North America (Safegraph 2021). Safegraph aggregates the data by category (e.g. Airports or Supermarkets) or brands (e.g. Costco or McDonald's) (Safegraph 2021). In addition, Baidu, a Chinese leading information technology (IT) company, offers location-based services to mobile devices for online searching and mapping based on the Global

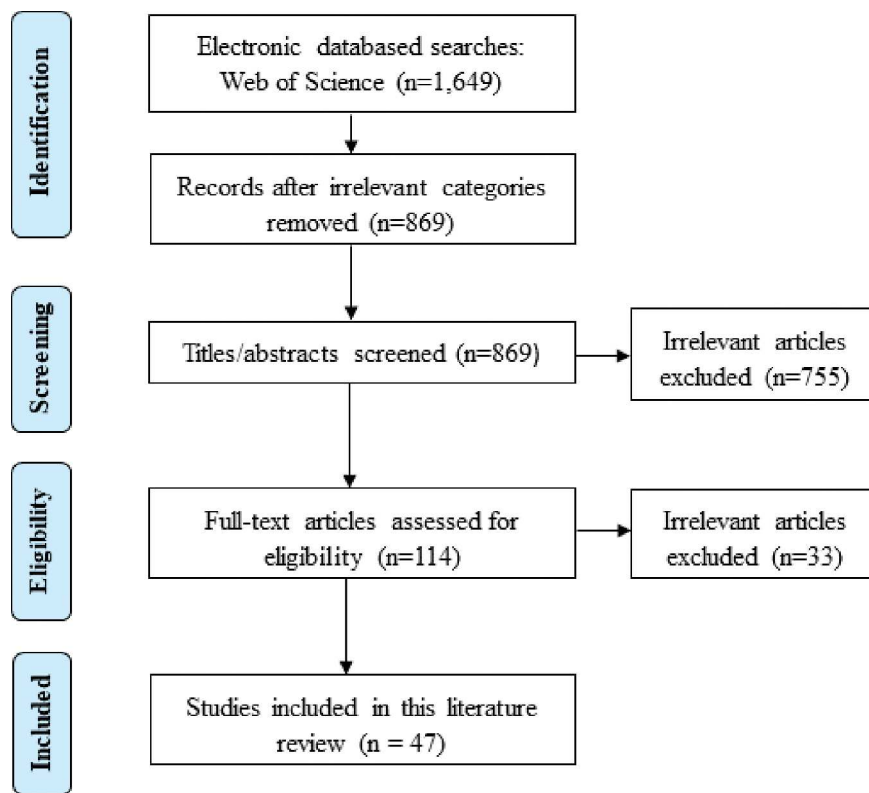


Figure 1. PRISMA flow chart on the identification and screening of studies on human mobility and COVID19 transmission.

Table 1. Inclusion and exclusion criteria of article selection.

Criteria	Definition
Inclusion	1) measure the association between human mobility and COVID-19 transmission, 2) measure the association between human mobility-related policies and COVID-19 transmission, and 3) apply quantitative methods.
Exclusion	1) measure the association between human mobility and other COVID-19 pandemic related issues, e.g. economic development, mental health, family relationship, 2) apply qualitative methods.

Positioning System, Internet Protocol addresses, locations of signalling towers, and wireless networks. Baidu Mobility Index contains daily inbound (i.e. percentage of people travelling to the city from all the cities in China) and outbound (i.e. percentage of people travelling from the city to all the cities in China) mobility data for all cities in China (except for Hong Kong, Macau and Taiwan) on each day from 1 January 2020 to 7 May 2020 (Liu et al. 2020). Baidu mobility data has been widely used to study population migration at the early stage of the COVID-19 outbreak in China. Similarly, Tencent is another Chinese leading IT company providing inter-city human mobility information by integrating air flight, train, and vehicle data. However, Tencent only released the inflow and out-flow data from 10 Chinese cities with the highest mobility index. Advantages of big data in human mobility include timeliness, cost-effectiveness, and large spatial coverage,

while its disadvantages vary across different data sources. For example, Google mobility data covers most countries worldwide, while Baidu and Tencent mobility data only covers Mainland China. Compared with Google mobility data, Baidu mobility data is relatively difficult to retrieve, requesting users to develop programs to access data, and the available data is restricted for a certain period. However, Google mobility data cannot indicate the inter-regional mobility flow that Baidu and Tencent mobility can do.

The second type of mobility data that has been widely used is the public transit data, collected through air flights. For example, Peirlinck et al. used the number of air passengers published by the Bureau of Transportation Statistics to model the spreading of COVID-19 across the U.S. (Peirlinck et al. 2020a; United States Department of Transportation n.d.). Public transit data has the advantage of compensating for the international or inter-regional mobility estimates, which cannot be revealed by Google mobility data. However, its key disadvantage is the roughness and availability at a relatively coarse scale, which cannot accurately simulate the spreading of COVID-19 at a fine scale.

The third category is census data, which records the number of people moving between or within administrative regions. For example, the United States Census Bureau publishes yearly geographic mobility dataset by

Table 2. Summary of mobility data sources used in the selected articles.

Category	Data Source	Link	Public accessibility	Spatial coverage	Time coverage	Update	Advantages	Disadvantages	ID of selected articles *
Big data	Baidu Mobility Index	https://qianxi.baidu.com/	N	City/Province (China)	2020.1.1 ~ 2020.5.8	Daily	Low costs; convenient in data gathering; available in inter-city mobility	Limited region coverage (China mainland); difficult to collect data	1, 15, 21, 41, 3, 44, 17, 28, 29, 45
	SafeGraph	https://www.safegraph.com/covid-19-data-consortium	Y	Census Block Group (North America)	Daily	Daily	Comprehensive users check-in information with high resolution; reaggregated to any spatial scale, such as census tract, county, and state; estimate human mobility inter/intro regions	Difficult to process because of large data volume; data is available after applying; it only covers the North American region	10
Public Transit	Google Mobility Report	https://www.google.com/covid19/mobility/	Y	County/State/Country (Global)	2020.1.1 ~ present	Daily	Wide region coverage; convenient in data gathering; low costs	Without inter-region mobility estimation	27
	Tencent Mobility Index	https://heat.qq.com/qianxi.php	N	city (China)	Daily	Daily	Real-time updates;	Difficult to collect data; only available at city level	7
	Airline Flight	N/A	N	County/State/Country (Global)			Convenient in data gathering; wide region coverage	Partially covering global flight information; only available in historical data; not publicly available	35, 42
Census		N/A	Y	County/State/Country	Yearly	Yearly	Low costs; convenient data gathering; precise results	Low update frequency	38
Survey		N/A	N		2019	N/A	High representativeness; low costs; convenient data gathering; precise results	Low update frequency	6, 27

* ID of selected articles was listed in Supplementary Table 1.

region and category, including race, sex, age, relationship to householder, educational attainment, marital status, nativity, tenure, and poverty status at the national, inter-state, intra-state, inter-county, and intra-county level (United States Census Bureau [n.d.](#)). When building epidemic models to estimate the effect of human mobility on COVID-19 transmission, Gatto et al. identified mobility fluxes at the municipal and provincial levels based on the 2011 commuting data from the Italian Census Bureau (Gatto et al. [2020](#)). Census data is representative, easy to access, and usually available at various spatial scales (e.g. county, state, and nationwide). However, census data is usually updated infrequently, and its data could be out-of-date and unable to reflect instant changes in human mobility with the rapid response to the implementation of mobility restrictions during the pandemic.

The fourth category is primary data, containing the participants' personal and location information collected through survey questionnaires. For example, DeFries et al. identified migration patterns over the last five years using a collected household survey covering 5,000 villages in 32 districts in central India (DeFries et al. [2020](#)). Zhang et al. analysed 1,245 contacts reported by 636 survey participants in Wuhan and 1,296 contacts reported by 557 survey participants in Shanghai to study the impact of social distancing and school closure on COVID-19 transmission. As a traditional source to track human mobility, survey data is relevant to the study objective. It covers those who are eliminated in the above secondary data resources, for example, those who do not use internet,

mobile phone, or air transportation. However, it is time-consuming and expensive to collect data, especially with a large sample size from various regions. Thus, it is an appropriate approach to measure human mobility in specific communities.

Our team published a literature review summarizing human mobility data that has been used in the COVID-19 pandemic which provides a more detailed and border discussion of various types of these datasets (Hu et al. [2021](#)).

3.2 Modelling approaches

The selected articles apply various mathematical modelling to analyse, simulate, and predict the association between human mobility and COVID-19. According to Siettos et al.'s categories of mathematical modelling of infectious disease dynamics, we categorized the mathematical models used in the selected articles into three categories: statistical method, mathematical/mechanistic state-space model, and simplified arithmetic model (Siettos and Russo [2013](#)). The category of these analytical models was presented in [Figure 2](#).

A total of 26 selected articles apply statistical methods, including correlation and exploratory analyses, as well as simple linear and advanced regression models. These models are mainly used in evaluating the effectiveness of social restriction policies and modelling the relationship between human mobility and COVID-transmission. The correlation and exploratory analyses conducted in these articles consist of Pearson correlation analysis (Chen et al., [2020](#); Zhang et al. [2020a](#)), rank-sum

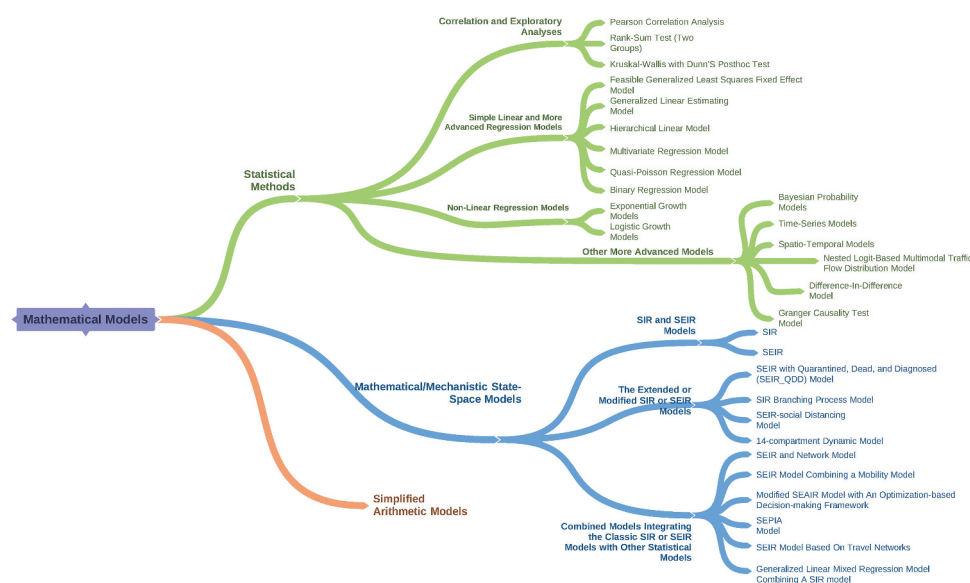


Figure 2. Summary of mathematical models applied in the selected articles.

test (two groups) (McGrail et al. 2020), and Kruskal-Wallis test with Dunn's post hoc analysis (McGrail et al. 2020). Other studies employ simple linear regressions models, including feasible generalized least squares fixed effect model (Yang et al. 2020b; Zhang et al., 2020c), generalized linear estimating model (Kraemer et al. 2020b), hierarchical linear model (Alfano and Ercolano 2020), multivariate regression model (Sirkeci and Yüceşahin 2020), quasi-Poisson regression model (Tobías 2020), and binary regression model (Yuan et al. 2020). These models are required to meet certain assumptions; for example, four assumptions are required to meet for linear regression models: the linear relationship between independent variables and dependent variables, residuals are independent, normally distributed, and have constant variance at every level of independent variables. If any of the assumptions is violated, the results maybe misleading. To address these issues from our selected articles, researchers applied non-linear regression models, including exponential growth models (Courtemanche et al. 2020; Djurović 2020) and logistic growth models (Aviv-Sharon and Aharoni 2020; Zou et al. 2020). Another stream of studies uses more advanced models to predict the future trend of COVID-19, including Bayesian probability models (Bherwani et al. 2020; Kaur et al. 2020), time-series models (Jia et al. 2020; Jiang and Luo 2020; Moosa 2020; Salje et al. 2020), spatial-temporal models (Dickson et al. 2020; Jia et al. 2020; Tian et al. 2020), nested logit-based multimodal traffic flow distribution model (Zheng 2020), difference-in-difference model (Banerjee and Nayak 2020), and granger causality test model (Zhao et al. 2020).

Mathematical/mechanistic state-space models (dynamic system models) are used in 21 selected articles. These models are commonly used in epidemiological studies to stimulate or predict the future trend of COVID-19 transmission with the inclusion of human mobility data as model parameters to optimize the modelling performance. Among those, Susceptible-Infectious-Recovered (SIR) and Susceptible-Exposed-Infectious-Recovered (SEIR) models (Balmford et al. 2020; DeFries et al. 2020; Neufeld, Khataee, and Czirok 2020; Rainisch, Undurraga, and Chowell 2020; Roda et al. 2020) are the most widely used models. Both SIR and SEIR models are used to predict the number of confirmed, susceptible, recovered cases, and deaths with the involvement of human mobility measures as independent variables or modelling parameters. Other studies employ the extended or modified SIR or SEIR models to improve the model performance (Ding and Gao 2020; Ngonghala et al. 2020; Sun et al. 2020; Yang et al. 2020a, 2020c), including SEIR with Quarantined, Dead, and Diagnosed (SEIR-QDD) model (H. Wang et al. 2020), SIR branching process model

(O'Sullivan et al. 2020), SEIR-social distancing model (Gupta, Jain, and Bhatnagar 2020), and a 14-compartment dynamic model (Westerhoff and Kolodkin 2020). The remaining articles utilize combined models integrating the classic SIR or SEIR models with other statistical models, including SEIR and network model (Peirlinck et al. 2020b), SEIR model combining mobility model (Linka et al. 2020), modified SEAIR model with optimization-based decision-making framework (Tsay et al. 2020a), SEPIA model (Gatto et al. 2020), SEIR model based on travel networks (Lai et al. 2020), and generalized linear mixed regression model combining SIR model (Zhang et al. 2020c).

Among the selected articles, one study uses a simplified arithmetic model (Killeen and Kiware 2020) with basic calculations (e.g. addition, subtraction, multiplication, division, rounding off, conditional statements, and unavoidable power terms) to ease the interpretability of the model. This model enables non-specialist readers to understand the process of modelling and in-depth inspect numerical predictions.

3.3 Study purposes and key findings

Though all the selected articles measure the association between human mobility and COVID-19 transmission, their specific aims can be categorized into 1) examining the effectiveness of policy-induced mobility control on COVID-19 (hereinafter referred to 'policy implementation and evaluation'), 2) predicting the COVID-19 dynamic through modelling or simulating human mobility (hereinafter referred to 'simulation and prediction'), and 3) comparing studies presenting the association between human mobility and COVID-19 across countries or regions (hereinafter referred to as 'cross-country /region comparison'). The key findings of each aim were presented below. Some articles may fall into more than one category if they contribute to each category equivalently.

3.3.1 Policy implementation and evaluation

The primary purpose of the selected articles focuses on estimating the influence of policy-induced human mobility on the transmission of COVID-19, particularly through assessing changes of mobility caused by social distancing, lockdown, and travel restrictions.

Findings from the policy-oriented papers show that policy interventions including lockdown, travel restrictions, social distancing, and border control have effectively reduced the transmission of COVID-19 (Chen et al. 2020; Djurović 2020; Jiang and Luo 2020; Tian et al. 2020; Yang et al. 2020b, 2020c). Articles focusing on the experience in Wuhan in China, where the first COVID-19 case

was reported, found that the lockdown order implemented in Wuhan substantially mitigated the spread of COVID-19 and delayed the growth of the COVID-19 epidemic in other cities in Hubei and other provinces in China (Chen et al. 2020; Jiang and Luo 2020; Kraemer et al. 2020a; Tian et al. 2020; Yang et al. 2020b; Zhang et al. 2020a). Moreover, many studies recognized China's response to COVID-19 that Wuhan's lockdown strategy has prompt, timely, and positive effects on controlling the spread of COVID-19 (Chen et al. 2020; Jiang and Luo 2020; Sun et al. 2020; Yang et al. 2020b). Similarly, in Europe, the effectiveness of lockdown policies on control the spread of COVID-19 has also been witnessed in Italy, Spain, and France (Dickson et al. 2020; Salje et al. 2020; Tobias 2020). Mobility restriction measures implemented in the U.S. also effectively decreased the spread of COVID-19, while an ongoing debate on the cost-effectiveness of mobility restrictions on mitigating the transmission of COVID-19 has been discussed considering its negative effects on economic activities (Tsay et al. 2020b). Many researchers expressed their concern about the potential danger of the rapid spread of the virus in the absence of these interventions (Banerjee and Nayak 2020; Courtemanche et al. 2020; Thunström et al. 2020).

The relationship between human mobility and the virus spread is temporal and spatial heterogeneity, along with observing a time-lag effect of mobility on the virus spread. Policy interventions, despite being globally effective in reducing both the spread of infection and its self-sustaining dynamics, have had heterogeneous impacts locally (Dickson et al. 2020; O'Sullivan et al. 2020; Zhang et al. 2020a). For example, large metropolitan areas encounter more disruptions and larger challenges to control infection because they cannot easily be broken down into separately managed regions (O'Sullivan et al. 2020). Labour-intensive cities in China need to take stronger measures to prevent a potential rebound in COVID-19 cases after releasing the restriction policies (Zhang et al. 2020a). Lockdown on public transport (e.g. auto, railway, coach, and flight) in China has the most prominent impact on virus control compared to lockdown on other public spaces (Zheng 2020). Researchers found in India that a prudent post-lockdown strategy might focus on easing physical distancing restrictions within high-risk places while maintaining restrictions between high-risk places (DeFries et al. 2020).

Moreover, policy measures need to be adjusted at different phases of the pandemic. In the initial stage of the outbreak, human mobility from Wuhan to other places in China was highly relevant to the growth rate of the COVID-19 cases in other cities and provinces. Still, this association became negative after the implementation of Wuhan lockdown and other national travel

restrictions (Kraemer et al. 2020a; Zhang et al. 2020a). Additionally, the reduction of infection caused by mobility control is observed to be relatively weaker in places where the outbreak occurred later (Zhang et al. 2020a). Furthermore, mobility control is observed to have a time-lag effect on the virus transmission and such effect varies across the geographic contexts and the timeline of the pandemic. In the U.S., researchers found that social distancing reduced the daily growth rate of confirmed COVID-19 cases by 5.4 percentage after one to five days but 9.1 percentage points after sixteen to twenty days (Courtemanche et al. 2020). Studies across various countries reported that the efficacy of lockdown continues to hold over two weeks or even up to 20 days after a lockdown was implemented (Alfano and Ercolano 2020; McGrail et al. 2020).

Scholars find that the timing, effectiveness, and stringency of policy implementation are crucial for the success of COVID-19 control efforts in different countries (Gupta, Jain, and Bhatnagar 2020; Ngonghala et al. 2020; Sun et al. 2020). The early implementation of social distancing and mobility restrictions is especially effective in lowering the spread of the coronavirus (Bherwani et al. 2020; Kaur et al. 2020; Sun et al. 2020; Yuan et al. 2020; Zhang et al. 2020a). Ngonghala et al. asserted that ensuring the high adherence/coverage of policy intervention and enhancing the effectiveness of such interventions is particularly important in control infection in the local community (Ngonghala et al. 2020). However, policymakers are more concerned about the public pressure towards lockdown mitigation as well as the downside of restrictive lockdown, for example, the tradeoff of social and economic upheaval (Westerhoff and Kolodkin 2020). For example, Tsay et al. suggested the 'on-off' policies alternating between strict social restriction and relaxing such restrictions can be effective at flattening the infection curve while likely minimizing social and economic cost, especially for the places where persistent small outbreaks oscillate between high-risk regions for many months (Tsay et al. 2020b).

3.3.2 Simulation and prediction

Another stream of the selected articles also measures the association between human mobility and COVID-19 transmission. Instead of analysing real policies and interventions, the authors simulate and predict the dynamics of COVID-19 applying various assumed human mobility-related measures (Gupta, Jain, and Bhatnagar 2020; Jia et al. 2020; Linka et al. 2020). Specifically, the authors quantified the COVID-19 pandemic by various mathematical/mechanistic state-space models as summarized in the modelling section (section 3.2), including epidemic models (Aviv-Sharon

and Aharoni 2020; Ding and Gao 2020; Djurović 2020; Gatto et al. 2020; Lai et al. 2020; Peirlinck et al. 2020b; Roda et al. 2020; Sirkeci and Yüceşahin 2020; Yang et al. 2020b; Zhao et al. 2020), spatial-temporal models (Bherwani et al. 2020; Jia et al. 2020; O'Sullivan et al. 2020), biological models (Westerhoff and Kolodkin 2020), and other advanced mathematical models (Killeen and Kiware 2020; Tsay et al. 2020a; Yang et al. 2020c). The common characteristic of these modelling approaches involves the measures of human mobility and social restriction policies as parameters in the modelling configuration.

Findings from the simulation models suggest that delay in start, less effective, or missing human mobility restrictions would increase the number of COVID-19 cases and deaths substantially (DeFries et al. 2020; Djurović 2020; Gupta, Jain, and Bhatnagar 2020; Jia et al. 2020; Peirlinck et al. 2020a; Sun et al. 2020; Zhang et al., 2020b). After comparing results based on various simulated interventions, the selected articles also indicate that early release of human mobility interventions could potentially increase the risk of the secondary outbreak (Neufeld, Khataee, and Czirok 2020; Yang et al. 2020b, 2020c). This prediction has already been proved in many countries. Considering socially and economically acceptability, selected studies also suggest implementing intermittent lockdown strategies (Westerhoff and Kolodkin 2020). Similar suggestions were reported by O'Sullivan et al. that they proposed regionally varying series of lockdown policies that offer advantages of less restrictive rules for part of the population (O'Sullivan et al. 2020).

During an ongoing pandemic, it is crucial but challenging for policymakers to make rapid and accurate risk assessments and implement suitable policies. The mathematical models applied in the selected articles bring various benefits to help policymakers and stakeholders to make decisions. First, policy interventions simulated in the models are adjustable which helps to evaluate various measures more cost-effectively compared with the traditional analytical approach. Second, the simulation and prediction models' predictive performance could be improved with updated data which increases the accuracy of prediction with the rapid changes of the pandemic. Third, the mathematical models can be updated by changing few parameters, which not only helps with the current pandemic, it could help policymakers to plan for future outbreaks.

3.3.3 Cross-country/region comparison

Another important purpose of the selected articles is to compare policy implementation responding to the pandemic, economic and financial consequences of

lockdown orders, and price of life comparisons across countries, regions, and cities. Such studies provide empirical evidence on the influence of human mobility on the COVID-19 in 8 countries (Balmford et al. 2020), 10 countries (Moosa 2020), across European countries (Linka et al. 2020), across Asian countries (Aviv-Sharon and Aharoni 2020), and between Wuhan in China and London in the UK (Yang et al. 2020c).

Several comparison studies reveal findings specific to different geographic contexts that have not been covered in the previous summary. In general, policy interventions may well explain the majority of cross-country variation in virus control in the initial stage of the pandemic (Balmford et al. 2020). However, these are less definitive conclusions if extended to a full spectrum of the pandemic. Mobility restriction policies implemented during the pandemic differ widely around the world. Policies that work well in one country may not be effective in other places. For instance, Kaur et al. indicated that countries that acted late in bringing in the policy intervention suffered from a higher infection rate than countries that reacted faster (Kaur et al. 2020). It is partially in line with the findings from a 10-country comparison that countries that have not imposed lockdown or have imposed lockdown either late or without stringency have performed poorly in infection control, except for Korea (Moosa 2020). The outbreak in Korea has been controlled rather well without a full lockdown, as Korea conducted a combination of interventions including border control, testing, tracing, the quality of the healthcare system, preparedness for epidemics and pandemics, and population density (Moosa 2020). Thus, when it comes to implementing different policy approaches to the pandemic, careful consideration of cross-country differences is required in terms of countries' nature as well as their demographic and socioeconomic variations. Yang et al. observed that China has efficient government initiatives and effective collaborative governance for mobilizing corporate resources to provide essential goods; however, this mode may be not suitable to the UK where it is more possible to take a hybrid intervention of suppression and mitigation to balance the total infections and economic loss (Yang et al. 2020c).

4. Discussion

This review summarizes findings from published papers measuring the association between human mobility and COVID-19 transmission at the early stage of the pandemic worldwide. The results indicate that early, timely, and consistent policy-induced mobility controls significantly reduced COVID-19 transmission. The application of simulation and predictions models increase the

flexibility and efficiency of policy analysis compared with traditional approaches, which could help researchers and stakeholders to make rapid and accurate risk assessment for the current and future outbreaks. Various types of mobility data have been used in selected articles. In addition to the traditional data sources including survey and census data, the majority of the studies applied publicly available data collected through public transit systems, mobile network operators, and mobile phone applications. More than half of these datasets were made available after the pandemic and many of these are free of access and use (Hu et al. 2021). The pandemic initiates an evolution of academic collaboration and data sharing that we encourage researchers and stakeholders to explore novel analytical approaches and datasets to combat the pandemic and prepare for future public health emergencies.

We summarized the suggestions for future studies from the included articles and recommended the following directions for COVID-19 studies: 1) to encourage multi-disciplinary collaboration with joint efforts from researchers with different backgrounds; 2) to adjust the implementation and stringency of mobility-control policies flexibly in correspond to the rapidly changing trend of COVID-19; 3) to improve the methods used in analysing, simulating, and predicting COVID-19 to be more realistic, context-specific, and temporal-specific; and 4) to enrich mobility data sources as well as improve data accuracy and suability for applications.

4.1 Multidisciplinary collaboration

Many topics of COVID-19 are connected through various disciplines, thus the scientific exploration of the pandemic needs collaboration from many areas including medical science, public health, geography, political science, economics, psychology, and environmental science. For example, many studies applied spatial analysis to understand COVID-19 distribution, which helps enable early assessments of the effectiveness of human mobility-related restrictions. This approach could further contribute to the exploration of health disparities, economic consequences, and recovery of the pandemic, if epidemiologists and geographers are coordinated effectively and efficiently. In addition, the scope of COVID-19 studies can be enriched by environmental scientists and climatologists to reveal the human-environment interaction which may affect virus transmission. For example, some studies have indicated that the transmission dynamics of COVID-19 was affected by weather, climatic conditions (Merow et al. 2020; Metalmann et al. 2021; Sil et al. 2020), and seasonality. Experts from physical

geography, meteorology, climatology, and environmental management would extend this avenue to broaden research dimensions and directions.

4.2 Policy adjustment

With an increasing number of countries experiencing the second/third wave of the pandemic, further work is needed to determine how to optimally balance the trade-off between economic loss and health outcomes of COVID-19 (Kraemer et al. 2020a). Policy interventions have been gradually upgraded with the rapid changes of the pandemic, which greatly promotes the arrival of the turning point of the epidemic (Jiang and Luo 2020). As such, rapid evaluations about the effectiveness of intermediate measures become important to control the social and economic cost, such as lifting a shelter-in-place order but requiring masks in public or opening restaurants at reduced capacity (Ngonghala et al. 2020).

Additionally, many studies did not control nor discuss the other covariates while measuring the association between human mobility and COVID-19 mitigation, including healthcare system, population density, and economic status, population, and housing density (Gupta, Jain, and Bhatnagar 2020; Moosa 2020), which need to be addressed in future studies. The resurgence of infection has also been observed to be associated with the release of national border controls (Moosa 2020); therefore, widespread decisive national action and international co-operation are required to conditionally reopen trade and travel between countries. Great caution is needed as gradual, exploratory steps towards reopening (Courtemanche et al. 2020), as even a slight relaxation of lockdown or importation controls may cause containment failure (Killeen and Kiware 2020). A combination of multiple interventions may achieve the strongest and most rapid effect on containing the spread of the virus (Aleta et al. 2020; Huang et al. 2021; Lai et al. 2020; Yin et al. 2021). Additionally, health education about the risk and severity of COVID-19 infection is needed to increase public's awareness (Ding and Gao 2020).

4.3 Methodological improvement

Mathematical modelling from the selected articles can be improved to identify and predict disease transmission. For example, the Epidemiological models (e.g. dominantly SEIR models) applied in the current articles can be improved by involving the measures of the effectiveness of policy implementation (Gupta, Jain, and Bhatnagar 2020), pharmaceutical factors (e.g. improved medical treatments, active immunity from vaccines, viral

mutation, increased likelihood of testing for subjects with more severe symptoms, the probability of changing antigenicity and virulence) (Tsay et al. 2020a), as well as the quantification of other non-pharmaceutical factors that are likely to contribute to control virus work, especially the isolation of suspected and confirmed patients and their contact (Tian et al. 2020; Yang et al. 2020a).

Another approach is to develop hybrid models across disciplines at multiple levels, integrating data in both spatial and temporal dimensions. Individual-level models need to include many patient-specific factors, including demographic and socioeconomic status (e.g. age-sex structure, ethnicity, and income) (Yang et al. 2020a; Zhang et al. 2020a). Aggregated-level models can extend to consider area-specific factors to distinguish heterogeneity within the regions (Alfano and Ercolano 2020; Dickson et al. 2020), including geographical and spatial characteristics (e.g. location, population, and housing density in a suburb) (Moosa 2020; Yang et al. 2020a) given the built environment in neighbourhoods where confirmed or suspected cases reside would affect the likelihood of infection (Gupta, Jain, and Bhatnagar 2020; O'Sullivan et al. 2020). Collectively, further research can be carried out in unifying temporary and spatial dimensions by distinguishing the different stages of pandemic and involving time-dependent parameters for a holistic understanding of the infection risk at hand (Bherwani et al. 2020; Peirlinck et al. 2020b; Sun et al. 2020).

In addition, there is a need to further improve the GIS-based framework and techniques of spatiotemporal analyses that have been used in the current mobility studies to integrate with the rapid development and recent advances of artificial intelligence (AI) techniques, including high-performance computing, storage, and data modelling (e.g. machine learning and deep learning methods (S. Wang et al. 2021)). For example, the establishment of geospatial AI (GeoAI) is a promising direction to create new databases (e.g. smart moving objects database) and to analyse complex human behaviours with unobserved confounders. Such a smart moving objects database has the capability to establish a more complex data structure and provide intelligent data extraction. In this way, mining and analysing mobility data can be extended from spatiotemporal attributes to sentiment and descriptive attributes to find the relationship between human mobility and subjective matters (e.g. personality and emotion) (Xu, Lu, and Güting 2019). GeoAI (e.g. machine/deep learning approaches) has brought on immense advancement in forecasting human behaviours based on historical mobility data (Hu et al. 2021). Future studies can extend along this direction to create intelligent geodatabases, and GeoAI-based

platforms, models, and systems that can be used in the diverse field of disease control and prevention, smart city planning, environmental management, and ecological conservation where human mobility intertwines with the surrounding space and social environment.

4.4 *Enrichment of spatial-temporal data*

Human mobility captured in the selected articles largely came from public sources, while these mobility data have some limitations which may impact their application. Some data are country-specific; for example, the Baidu migration data is only available in China (Yuan et al. 2020). Additionally, mobility data retrieved from mobile phones or mobile app users designed by large companies encounter data biases in population coverage, which may exclude some specific subgroups, particularly children and aged populations who may not use mobile phones (Banerjee and Nayak 2020; Lai et al. 2020). The index-based mobility data (e.g. provided by Google, Baidu, and Apple) does not include population inflow to and/or outflow from a given place. Alternatively, user-based social media big data (e.g. geotagged Twitter data) is able to indicate the inter-regional movement to improve the accuracy of models (Gupta, Jain, and Bhatnagar 2020; Huang et al. 2020; O'Sullivan et al. 2020; Tsay et al. 2020a), although such data is not used in the selected studies. With the technological advancements and the emergence of further refined data, it will be interesting for future studies to involve additional data, to use a combination of multi-sourced data, and to compare the reliability and quality of data (Banerjee and Nayak 2020; Li et al. 2021; McGrail et al. 2020). Moreover, data sharing and information disclosure are encouraged for future studies. Some scholars and institutes have put great efforts into collecting, collating, and sharing data via crowdsourcing and cloud platforms to facilitate cross-disciplinary collaborations. For example, Harvard Dataverse provides an open online data management and sharing platform for COVID-19 studies with daily COVID-19 confirmed cases, global news, social media data, population mobility, climate, health facilities, socioeconomic data, events chronicle, and scholarly articles (Hu et al. 2020).

4.5 *Limitation*

The study has limitations that should be noted. First, we did not include non-peer-reviewed articles (e.g. working papers and preprints) in this review. Traditional peer review usually takes months from submission to publication, while timely reporting of research findings is a priority during the pandemic, which dramatically increased the use of preprint service (Jung, Sun, and

Schluger 2020). Though preprints provide direct and rapid access to information, criteria used to justify preprints are not available. Thus, we only searched for published and early access articles, which inevitably exclude the findings from some popular non-peer-reviewed articles. Second, this review includes a small number of eligible articles focusing on Africa and South America which could be due to the late appearance of the first case in some regions as well as the limited funding and resource to conduct COVID-19 related research. Third, our search captured publications at the early stage of the pandemic that obtained limited articles of the second and third waves of the pandemic, which has been observed in several countries after lifting mobility restriction policies. The findings summarized in this review may not well explain the resurged cases or the cases via converted transmission over a long time. Additionally, our searching was completed through a single database (WoS), which does not index all journals, and many papers from the indexed journals may take several months or years to be added to the database. These restrictions may impact our searching results. Thus, we encourage future researchers to extend our systematic review to cover a longer period and include the most updated results from published and preprint articles from various regions and databases.

5. Conclusion

Understanding the pattern of human mobility is essential to prevent and predict the spread of infectious diseases. As COVID-19 continues to spread and resurge across countries, we summarized data and analytical models used in publications related to human mobility and COVID-19 transmission. The authors applied various models, including statistical models, mathematical/mechanistic state-space models, and simplified arithmetic models to examine the relationship between human mobility and COVID-19 transmission, using multi-sourced spatial-temporal mobility data. The findings on policy implications summarized herein provide important guidance in making, implementing, and adjusting current and post-pandemic measures. What we have seen in existing studies is the relationship between human mobility and the virus spread is temporal and spatial heterogeneity, along with the observation of a time-lag effect of mobility on the spread of the virus. Additionally, this relationship is stronger in the initial stage of the pandemic but less conclusive if extending to a full spectrum of the pandemic or different geographic contexts. What we have not seen from the current publications motivates us to propose future research directions. Specifically, we suggested that

governments promote prompt and sustainable measures to control the spread of COVID-19. We also encourage multi-disciplinary collaborators to conduct rapid and accurate risk assessments of the pandemic by incorporating rich data sources and improving spatial-temporal modelling to prevent and predict future outbreaks.

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