ORIGINAL - SURVEY OR EXPOSITION

# Data analytics during pandemics: a transportation and location planning perspective

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## Abstract

The recent COVID-19 pandemic once again showed the value of harnessing reliable and timely data in fighting the disease. Obtained from multiple sources via different collection streams, an immense amount of data is processed to understand and predict the future state of the disease. Apart from predicting the spatio–temporal dynamics, it is used to foresee the changes in human mobility patterns and travel behaviors and understand the mobility and spread speed relationship. During this period, data-driven analytic approaches and Operations Research tools are widely used by scholars to prescribe emerging transportation and location planning problems to guide policy-makers in making effective decisions. In this study, we provide a review of studies which tackle transportation and location problems during the COVID-19 pandemic with a focus on data analytics. We discuss the major data collecting streams utilized during the pandemic era, highlight the importance of rapid and reliable data sharing, and give an overview of the challenges and limitations on the use of data.

**Keywords** Transportation · Location · Data-driven analytics · Pandemic · COVID-19

## 1 Introduction

The 21st century has witnessed significant changes in several aspects of life, including trends in urbanization, travel, logistics, and commerce, that also increase the risk of mass disease outbreaks that can be amplified into epidemics and pandemics. Epidemic and pandemic outbreaks are serious health concerns that can cause major life losses and undesirable health

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conditions. Killing more than 50 million people, the 1918 influenza pandemic is considered as the most severe pandemic in recent history (Morens and Fauci 2007).

The recent pandemic outbreak, COVID-19, once again showed how public and social life globally is still vulnerable to the influenza threat. The fast-spreading novel coronavirus originated from Wuhan, Hubei province of China was first reported in December 2019. As of January 23rd, 2022 it infected 350 million people and claimed more than 5.6 million lives (Worldometers 2022). Its high spread speed coupled with the severe consequences on human health led to major transformations in several aspects of community's lifestyle.

One of the foremost impacts of the disease to social life is observed on the mobility behaviors of the population. The increase in the mobility needs of individuals due to social and economic factors in the last decade yielded much dense intra-city and inter-city traffic. This made the task of preventing and controlling pandemic in metropolitan cities even harder due to their high populations, human mobility and frequency of contact. This increase is also boosted by the expansion of supply chain networks at the global scale. As a result of the pandemic pressures and governmental actions (e.g., urban lockdowns, quarantines, school closures, travel ban), mobility and all forms of traffic both in urban and metropolitan areas decreased substantially. The change in the intensity of dwelling and work, directly affected the movement behavior of individuals. The World Health Organization (WHO) emphasizes that mobility restriction measures together with infection prevention and control measures play an important role in reducing the number of cases, hospitalizations, and deaths (WHO 2021).

The global burden of COVID-19 pandemic has also caused pressure on governments and policy makers to devise innovative and effective transportation decisions while ensuring public health. Apart from conventional decision problems and solution approaches, they face several novel problems in location and transportation planning domains. The novelty in these problems is mainly rooted in the sudden changes in mobility, the increase in demand for delivery systems, and various governmental restrictions on travel which impact the transportation and location of people, materials, and facilities. The uncertainty associated with the disease spread speed and lack of accurate and timely mobility data pose further challenges to planners and researchers.

One of the prevalent causes of transportation related planning problems is the excessive increase in logistics and delivery systems. Social distancing measures, stay-at-home and quarantine orders triggered a sudden increase in daily necessities of the population. The pandemic also caused disruptions in medical supply chains by the huge amount of personal protection equipment, test kit, hygiene kit, vaccine, etc. demand worldwide. This revealed a number of routing problems in the context of food delivery, e-commerce delivery, daily needs delivery, use of emergency vehicles, intelligent transportation systems, and robots for delivery.

It would be a glaring omission to handle operational and tactical level transportation problems without considering the effect of location decisions at the strategic level. Adopting a more holistic perspective, policy makers seeked ways of developing effective supply chain networks by integrating location-related decisions to their design problem. Some examples include test center location and routing problems for managing mobile test personnel, design of vaccine depot locations within the cold supply chain network, determining the location and capacity of regional food hubs, etc.

The social and economic effects of the pandemic, escalating with the intensity of the measures taken, keep shaping the spread of COVID-19 disease as well as travel habits. A century ago, the world's most valuable resource was oil. But today, as also observed by Economist (2017), the resource in question is *data*. To gain better understanding of the

relationship between mobility and disease spread, and consequently make better decisions, reliable data is crucial. This necessity is one more time recognized by governments and private companies in fight with the COVID-19. The extraordinary volume of data generated during the pandemic spread is growing exponentially over time. Various data types (deaths, confirmed cases, public transportation density, high risk areas, etc.) collected by different data streams (mobile networks, transportation systems, etc.) at different time frames constitute the backbone of analytic approaches. An effective transportation and location plan can only be devised by the implementation of data-driven analytics. Studies show that if governments can accumulate and process mobility data from various sources to generate realistic predictions on human mobility and disease spread, they are more likely to ameliorate the negative impacts of the pandemic and restore to the normality quickly (Jia et al. 2020).

Based on these enlightening experiences of data-driven decision-making processes observed during the COVID-19 pandemic, in this study we focus on the data analytics in the context of transportation and location planning. Considering that data-driven Operations Research (OR) tools have been successfully implemented to alleviate the adverse effects of the spread, we investigate the main research problems observed during the pandemics from the OR perspective. To achieve this, we review and discuss the emerging decision problems as well as solution techniques arising in the transportation and location planning domains during pandemics. Motivated by the role of data in making better decisions during the pandemic, in our discussions, we adopt a data-oriented perspective and focus on the main streams for location and transportation data during pandemics.

The organization of this paper is as follows. In Sect. 2 we provide a detailed discussion on our literature review in five topics. We first discuss our survey methodology and report some useful statistics and quantitative results. Next, we give an overview on the problem domains, decision problematics, and solution approaches in the context of our research. Next, in Sect. 3 we discuss the data collecting streams related to mobility and transportation during pandemics/epidemics. In Sect. 4 we briefly discuss the challenges and limitations in the use of mobility data. Finally, we conclude in Sect. 5.

## 2 Review of the literature

In this section, we provide the review of the literature with a particular focus on data collection streams. Data constitutes the core of the analysis, hence, is a prerequisite for an efficient and reliable decision support. Having said that, in our review, we aspire to answer the following research questions:

- RQ1. What are the main themes and contents of the transportation and location planning studies during pandemics from the OR perspective?
- RQ2. Which decision problems emerge and which solution methods are utilized to address emerging problems in the transportation and location planning domain during pandemics?
- RQ3. From the data-oriented perspective, what are the main streams for obtaining location and transportation data during pandemics and pertaining characteristics, applications, and challenges?

The following subsections review the body of literature systematically in an effort to answer the abovementioned research questions.

**Fig. 1** Operations research flowchart for pandemic/epidemic planning to identify emerging location and transportation problems

## 2.1 Survey methodology

In this study, we used mainly two prominent databases, *ScienceDirect* and *IEEE Xplore*, to search and explore articles that are relevant to the scope of our survey. We initially generated a list of studies using keywords ("transportation" OR "location") AND ("COVID-19"). This initial list comprised of a total of 854 studies which were published in 2020 and 2021 (and those in press). Then, we performed a pre-screening of all papers in the list with respect to their scope, topic, abstract and content, and reduced the set to 224 articles. In particular, we included studies related to the fields of transportation systems, transportation networks, pandemic and epidemic planning, and transportation problems observed during pandemics solved with OR tools. A flowchart of our survey methodology is depicted in Fig. 1.

In an effort to elicit as much information as possible from the existing research, studies have been examined in multiple dimensions which are given below.

– Country: The country where the data of the case study are obtained. If not reported, country of the first author is considered.
– Publication: The name of the publication (journal or conference proceedings) where the paper was published.
– Problem domain: The problem domain of the study. As will be discussed in detail later, we defined six major problem domains as: (*i*) effects of pandemic on transportation, (*ii*) effects of mobility on pandemic spread, (*iii*) planning of logistic operations and delivery systems during pandemics, (*iv*) medical waste management during pandemics and wastewater-based epidemiology, (*v*) vaccine planning and distribution models, and (*vi*) social distancing related studies.
– Decision problematic: The decision problem tackled in the study. In our review we defined a total of 16 decision problematics some of which include travel mode/choice and population mobility estimation, disease spread modeling, travel demand prediction, vaccine planning, supply chain design problems, transportation and routing of medical waste.
– Solution method: The solution method, technique or approach employed to address the problem under study. We categorize studies with respect to the solution method such as data analysis, mathematical modeling, simulation modeling, multi-criteria decision making, etc.
– Data collection stream: The classification of the data used in the study in terms of data source and the way the data is obtained. In particular we defined four streams as: (*i*) Public transportation systems, (*ii*) surveys, (*iii*) mobile phone applications, (*iv*) mobile network operators.

Our survey methodology is in line with the sequential literature survey structure depicted by Templier and Paré (2015). In particular, firstly, we formulate the research questions that we
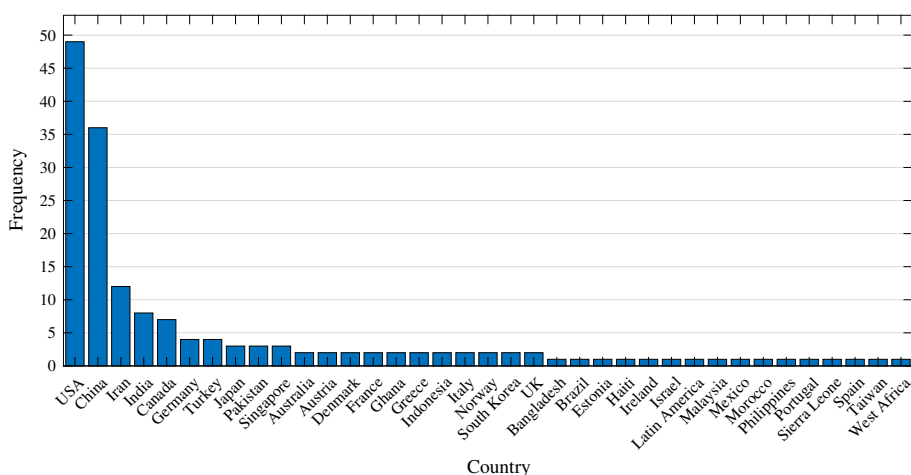
**Fig. 2** Number of studies with respect to the countries

desire to address with our survey. Then, we search the extant literature as comprehensive as possible to ensure that all related studies are covered. A screening step follows for evaluating the applicability of studies obtained in the previous step. After screening, all remaining studies are assessed for scientific quality. Once the final set of studies are obtained via previous steps, the relevant data are extracted. To organize data extraction process, we determine multiple dimensions within which all papers are examined. Lastly, all extracted data are analyzed and presented to the reader. As Templier and Paré (2015) remarks, a review's quality and coherence emerge from the application of a structured approach with specific guidelines. Keeping this reality in our minds, we follow the aforementioned framework that allows us to organize our survey and convey valuable information to the potential reader.

## 2.2 Quantitative results

We start our review of the existing literature by providing quantitative information in terms of country and publication review dimensions. Figure 2 shows the number of studies with respect to the origin of the countries. The figure reveals that, the USA and China contribute to the body of relevant literature most with 49 and 36 publications, respectively. They are followed by Iran (12 publications), India (8 publications) and Canada (7 publications). These results are intuitive since the USA, China, Iran, and India are among those countries that the COVID-19 pandemic struck the most.

163 out of 167 articles have been published in journals while the remaining four appeared in conference proceedings. Table 1 gives the number of studies published in different journals in decreasing order. *Transport Policy* and *Transportation Research Interdisciplinary Perspectives* share the first place with 20 articles published in the topic of interest. *Sustainable Cities and Society*, *European Journal of Operational Research*, *Transportation Research Part A: Policy and Practice* and *Transportation Research Part C: Emerging Technologies* are the next four journals with 9, 7, 6, and 6 published articles, respectively.

In addition, while examining transportation and location problems, we also included a few studies applied in past pandemic/epidemics apart from the COVID-19 outbreak (i.e., Influenza, Ebola virus disease, SARS disease, Cholera disease). This is because we observe

**Table 1** The number of studies published in different journals

| Journal | Frequency |
| --- | --- |
| Transport Policy | 20 |
| Transportation Research Interdisciplinary Perspectives | 20 |
| Sustainable Cities and Society | 9 |
| European Journal of Operational Research | 7 |
| Transportation Research Part A: Policy and Practice | 6 |
| Transportation Research Part C: Emerging Technologies | 6 |
| Computers & Industrial Engineering | 5 |
| Journal of Transport & Health | 5 |
| Transportation Research Part E: Logistics and Transportation Review | 5 |
| Applied Soft Computing | 4 |
| Journal of Air Transport Management | 4 |
| Journal of Transport Geography | 4 |
| Science of The Total Environment | 4 |
| Cities | 3 |
| International Journal of Production Economics | 3 |
| Journal of Urban Economics | 3 |
| Journal of Urban Management | 3 |
| Applied Geography | 2 |
| Health & Place | 2 |
| Heliyon | 2 |
| International Journal of Transportation Science and Technology | 2 |
| Journal of Cleaner Production | 2 |
| Research in Transportation Economics | 2 |
| The Lancet Digital Health | 2 |
| Vaccine | 2 |
| Annals of Operations Research | 1 |
| Case Studies on Transport Policy | 1 |
| Computer Methods in Applied Mechanics and Engineering | 1 |
| Computers, Environment and Urban Systems | 1 |
| Construction and Building Materials | 1 |
| Data & Knowledge Engineering | 1 |
| Energy Research & Social Science | 1 |
| Engineering Applications of Artificial Intelligence | 1 |
| Environment International | 1 |
| Epidemics | 1 |
| Healthcare | 1 |
| IATSS Research | 1 |

**Table 1** continued

| Journal | Frequency |
| --- | --- |
| IEEE Control Systems Letters | 1 |
| IEEE Engineering Management Review | 1 |
| International Journal of Applied Earth Observation and Geoinformation | 1 |
| International Journal of Computational Intelligence Systems | 1 |
| International Journal of Hygiene and Environmental Health | 1 |
| Journal of Advanced Research | 1 |
| Journal of Biomedical Informatics | 1 |
| Journal of Economic Behavior & Organization | 1 |
| Journal of Infection and Public Health | 1 |
| Journal of Outdoor Recreation and Tourism | 1 |
| Journal of Public Economics | 1 |
| Journal of Traffic and Transportation Engineering (English Edition) | 1 |
| Mathematical Problems in Engineering | 1 |
| Pervasive and Mobile Computing | 1 |
| Procedia Computer Science | 1 |
| Procedia Engineering | 1 |
| Process Integration and Optimization for Sustainability | 1 |
| Resources, Conservation and Recycling | 1 |
| Smart Health | 1 |
| Transportation Research Part B: Methodological | 1 |
| Transportation Research Part D: Transport and Environment | 1 |
| Transportation Research Part F: Traffic Psychology and Behaviour | 1 |
| Travel Behaviour and Society | 1 |
| Travel Medicine and Infectious Disease | 1 |
| Total | 163 |

that 'vaccine planning models' and 'logistics and delivery systems' are based on previous studies when examining COVID-19 studies. Thus, we have also included 8 of the most cited studies. Although the number of studies revealed with the COVID-19 outbreak is quite high (93.8%), the studies on Influenza (2.5%), general pandemic models (1.8%), Ebola virus disease (1.2%) and Cholera disease (< 1%) are included in the reviewed papers.

## 2.3 Problem domains

In our detailed examination of 167 relevant papers, six main problem domains that studies can be classified into have become evident: (*i*) effects of pandemic on transportation, (*ii*) effects of mobility on pandemic spread, (*iii*) planning of logistic operations and delivery systems during pandemics, (*iv*) medical waste management during pandemics and wastewater-based epidemiology, (*v*) vaccine planning and distribution models, and (*vi*) social distancing related studies. Table 2 provides the breakdown of papers on these problem domains. This table shows that, the majority of the papers have focused on the *effects of pandemic on transportation* problem domain, which accounts for the 41.3% of the papers. Studies that fall into *logistics*

**Table 2**  The number of studies published with respect to problem domains

| Problem domains | Frequency |
| --- | --- |
| Effects of pandemic on transportation | 69 |
| Logistics and delivery systems | 36 |
| Effects of mobility on pandemic spread | 35 |
| Medical waste management and wastewater-based epidemiology | 10 |
| Vaccine planning models | 10 |
| Social distancing models | 7 |
| Total | 167 |

*and delivery systems* and *effects of mobility on pandemic spread* follow these domains with a count of 36 and 35, respectively. Conversely, among these five problem domains, *social distancing models* seems to have drawn the least attention among researchers dealing with the topic. Below, we explain these problem domains (RQ1).

• **Effects of pandemic on transportation:** The COVID-19 pandemic had unprecedented and unpredictable effects on transportation all around the world due to the severe decline in the number of passengers. Mobility restrictions, remote working, social distancing, quarantine, and lockdown measures can be mentioned among the main reasons that lead to the dramatic decrease in the number of passengers both in inter-city and intra-city travel. In this regard, transportation systems have required reliable and timely predictions of passenger demand, in an effort to make efficient transportation planning. As the dynamics and means of pandemic spread have become evident to the public, the nature of public transportation has changed and adapted rules of *new normal*, such as wearing masks, keeping social distance, and controlling congestion in vehicles and in crowded transportation stations. Conversely, dramatic changes have been observed in travel modes/choices of individuals. For example, use of micro-mobility vehicles/services (e.g., bicycles, shared bicycles, scooters, electric scooters, electric skateboards), motorcycling, and walking have become safer alternatives for individuals. Additionally, more people have utilized private vehicles to commute, which has led to a decrease in public transportation revenue.

Considering that it may take some time for almost all mass transportation industries to fully recover, it is crucial to understand the impact of pandemic spread and following governmental regulations on the travel preferences of the population. These factors and emerging problems have drawn the attention of many researchers and yielded the majority of the publications that are considered in this review. To give the reader a better understanding of the problems tackled in this problem domain, exemplary case studies addressed by the researchers are listed below.

– Analyzing the effect of the US air transportation restriction measures implemented during the COVID-19 pandemic from passenger perspective (Monmousseau et al. 2020)
– Measuring the transit/metro riders' travel patterns and changes before and after COVID-19 in Hong Kong, China (Zhou et al. 2021b)
– Comparison of bike-sharing and subway usage patterns during the COVID-19 lockdown in 2019 in New York City (NYC) (Wang and Noland 2021)
– Analysis of the voluntary reductions in human mobility during the initial stage of the COVID-19 (Mendolia et al. 2021)

– Analysis of people's mobility-styles and habitual travel behaviors in Chicago during the COVID-19 pandemic (Shamshiripour et al. 2020)

• **Logistics and delivery systems:** Due to its long-term disruption existence, high uncertainty, and ripple effect, the COVID-19 outbreak posed a big threat to many industries relying on material flow through supply chains. Logistics and delivery systems are among those sectors that experienced the severest disruptions during the pandemic.

Conventionally, the risks in supply chains and delivery systems are categorized as operational and disruption risks. The operational risks are basically related to daily disturbances (e.g., lead time, fluctuations in demand) among the chain, whereas disruption risks are concerned with low-frequency and high-impact occurrences (e.g., natural disasters, man-made catastrophes, legal disputes, or strikes) (Tang 2006). The pandemic/epidemic outbreaks are considered as a special case of supply chain. Different from the other two risk categories, they mostly start at a small scale, but disperse over large regions very fast. Pandemic/epidemic outbreak risk can be characterized by three components as: (*i*) the existence of long-term disruption in uncertain scales, (*ii*) ripple effect through the supply chain and population, and (*iii*) simultaneous disruptions in demand, supply, and all kinds of logistics infrastructure (Ivanov 2020).

Unprecedented and unforeseen effects of the pandemic caught the sector unprepared, however, thanks to the OR/MS tools and techniques, logistics and delivery firms have adapted themselves to the new normal. These tools and techniques have been used to assist managers, planners, and decision-makers in describing, predicting, and prescribing the impact of disease on the supply chain operations. Our review of literature also revealed that some of the most common questions that are tackled are, "How long can a supply chain sustain a disruption?", "How long time is needed for a supply chain to recover after a pandemic outbreak?", "What is the best policy to mitigate the adverse effect of pandemic on the supply chain?".

In the new normal, the logistics and delivery systems need to develop resilience strategies to overcome problems that stem from the uncertainty in demand and production, additional hygiene measures, panic buying, and fluctuations in purchasing patterns. Apart from the problems encountered in the conventional logistics and delivery operations, several new problems related to healthcare supply chain operations also emerged during the pandemic, such as routing of emergency vehicles, allocation and distribution of medical supplies from hubs to hospitals, and determining the locations of vaccine centers. Automatic driving technology has also been transformed by the use of autonomous vehicles and drones for healthcare services (Yang 2022). These vehicles can be used for contactless delivery services, which reduce labor and epidemic risk and improve safety (Bozkaya et al. 2020).

We observe that the main focus of the reviewed articles in this problem domain is to create resilience strategies to overcome emerging healthcare supply chain operation problems due to COVID-19 pandemic (Chowdhury et al. 2021). Exemplary case studies tackled in this category are listed below.

– Developing facemask supply and demand strategy during COVID-19 pandemic in Australia (Rahman et al. 2021)
– Estimating the excess demand for products and services during the pandemic (Nikolopoulos et al. 2021)
– Determining the location of distribution centers and optimizing the inventory management during the COVID-19 pandemic in Tehran, Iran (Goodarzian et al. 2021)
– Route planning of autonomous test vehicles in Brant, Ontario to find the optimum number of stops for the test time (Simsek et al. 2021)

- Estimating the daily number of emergency ambulance dispatches for the pre- and ongoing COVID-19 pandemic periods in Nagoya City, Japan (Rashed et al. 2021)
- Management of healthcare resources and planning hospital locations during the pandemic in Wuhan, China (Eriskin et al. 2022).

● **Effects of mobility on pandemic spread:** It is well-known that respiratory fluids can be contacted through droplets produced by coughing, sneezing, or breathing and by touching on contaminated surfaces with hands. In this regard, human mobility serves as a significant means for the spread of the pandemic since it increases the probability of contacting with some other individual who is infected. Hence, restricting human mobility is considered as an efficient strategy utilized by many governments to reduce the spread speed of disease. The degree of dependency between the spread of the pandemic and human mobility is peculiar to countries due to the different social-cultural structures, geographical locations, and welfare levels. Therefore, investigating the spatial-temporal pattern of mobility and identifying the associations of mobility with the pandemic spread dynamics have been one of the most investigated domains.

For this purpose several data-driven analytic approaches have been implemented by scholars to represent the impact of mobility to disease spread. Several models which aim to capture this relationship at both local and global scale by incorporating the heterogeneity, complex mobility behavior of population and contact patterns. Our review of literature also reveals that these models are successfully used by planners in making decisions on mobility restriction of people. Exemplary case studies tackled in this category are listed below.

- Understanding the association between the spread dynamics of infectious diseases and the mobility dynamics through urban transportation systems in NYC (Qian and Ukkusuri 2021)
- Development of a decision support framework that considers the lockdown of cross-border traffic, internal traffic and movement within population in Germany (Ding et al. 2021)
- Examining travel behavior and its relationship with COVID-19 cases in the early stages of the outbreak in US counties (Brinkman and Mangum 2021)
- Evaluating the impacts of migration flows and transportation infrastructure in the context of COVID-19 transmission in China (Li and Ma 2021)
- Exploring the spatial-temporal pattern of mobility and identifying the associations of mobility with COVID-19 cases (Tokey 2021).

● **Medical waste management and wastewater-based epidemiology:** With the emerge of the COVID-19 pandemic, the amount of medical waste has grown in all over the world. Due to the infectious nature of the medical waste, poor waste management poses a great danger to healthcare personnel, medical waste workers, and patients. Moreover, these wastes (i.e., facemask, disinfectant) are now generated not only at medical centers but also at homes, schools, and restaurants (Barma and Modibbo 2021). Moreover, improper handling or disposal of medical waste may lead to environmental pollution. Therefore, timely collection, transportation, treatment, and disposal of medical waste are vital to contain the spread of the virus. Having said that, we have observed a remarkable increase in the number of studies on medical waste management during the COVID-19 pandemic. Studies which tackle wastewater management problems in the context of pandemics strongly rely on data such as the topological data of sewer network, city parcels, cadastral data, population, demographic and socioeconomic indicators.

Conversely, wastewater-based epidemiology has been one of the research topics within public health surveillance addressing near real-time monitoring of the existence of SARS-

CoV-2 virus in the faeces of infected individuals. In this regard, there exists an increase in the number of wastewater-based epidemiology studies that seek to detect the presence and diversity of the SARS-CoV-2 virus in wastewater in a timely and cost-effective manner. Determining the optimal monitoring sites (sensor placement) for SARS-CoV-2 surveillance, identifying target population clusters, and forecasting the number of COVID-19 infections based on the the SARS-CoV-2 concentration in wastewater have emerged as important location and transportation related research topics in this domain. Exemplary case studies tackled in this category are listed below.

– Optimal selection of monitoring sites for SARS-CoV-2 surveillance in the sewage network of Girona, Spain (Calle et al. 2021)
– Identifying target population clusters and optimizing locations for the implementation of wastewater-based epidemiology (Rallapalli et al. 2021)
– Forecasting the number of COVID-19 infections based on SARS-CoV-2 wastewater concentrations (Cao and Francis 2021)
– Infectious waste location-routing management for waste collection, transportation, treatment, and final disposal in Wuhan, China (Zhao et al. 2021)
– Analysis of waste management in Wuhan, China in terms of generation, transportation, and disposal of medical waste (Chen et al. 2021a).

● **Vaccine planning models:** Limited stocks of vaccines, medicines, and other medical resources pose a healthcare delivery challenge during the COVID-19 pandemic. Once the vaccination process has been inaugurated worldwide, planning for mass vaccination and immunization has become an important aspect of pandemic management.

Rastegar et al. (2021) defines the main stages (and relative decision problems) of a vaccine supply chain with four steps as: (*i*) product (determining the type of vaccine to be produced), (*ii*) production (determining the time and number of vaccines to be produced), (*iii*) allocation (determining the receiving individuals of the vaccines), and (*iv*) distribution (determining the best way of distributing the vaccines). During the COVID-19 billions of people worldwide have reached vaccines of different types. The biggest challenge faced in vaccine distribution supply chains is caused by the different transportation, storage, and handling requirements of each vaccine type. For example, cold supply chain requirements, expiry dates, vaccine vial monitor categories, number of doses needed, target population characteristics, etc. require strict supply chain operations for effective management of distribution, logistics and vaccination practices.

A successful vaccine supply chain is expected to meet the demand by guaranteeing the availability of the number and type of vaccines at specified vaccination centers in potent conditions and at an affordable cost (Brison and LeTallec 2017). Through our systematic review of the relevant body of literature, we observed that several researchers have tackled the problem of developing efficient supply chains consisting of manufacturing plants, vaccine storage depots (hubs), vaccination centers, and optimal distribution of the vaccine to potential demand points. Exemplary case studies addressed in this problem domain are listed below.

– Identifying key challenges for planning, evaluating, and modeling vaccine efficacy trials for emerging pathogens (Madewell et al. 2021)
– Dynamic COVID-19 vaccine distribution (Albahri et al. 2021)
– Fair distribution of the flu vaccine to potential vaccine recipients during the fall and winter flu season in Iran (Rastegar et al. 2021).

● **Social distancing models:** One of the effective measures for preventing pandemic spread is to keep social distance among individuals. After the early lockdown stages of the COVID-19 pandemic, many countries relaxed their strict mobility measures and allowed certain

businesses to continue their operations with certain constraints. Among those constraints, social-distancing aims at decreasing the contact among people by encouraging them stay at home as much as possible. As another term, "physical distancing" (sometimes used instead of social distancing) is used to reinforce individuals to stay away (mostly at least 6 feet while wearing face masks) from others to slow down the disease spread speed.

Hence, the social distancing requirement introduced a number of location planning problems which mostly aim at maximizing the number of people that can be fitted inside a facility while satisfying the social distancing requirement. To that end, social distancing models have been proposed for different confined and public areas. Some examples include fitting customers in a restaurant, workers in an office, and people in a theater. Within the scope of our review, pertaining studies mostly focus on congestion control in public transportation vehicles and the optimal layout (seat assignment) of passenger seats. These problems are mostly tackled as a special case of circle-packing optimization models (Fischetti et al. 2021).

The uncertainty and non-linearity in the virus spread risk coupled with the the heterogeneity of the population constitute the major challenges in making effective social distancing related decisions. The problem of area utilization maximization while minimizing infection risk also relies on accurate data such as interference function, infection dynamics, virus spread speed, travel habits of individuals, demographics, population, etc. Some of the problems addressed in this category are presented below.

- A survey on user and operator compliance on using facemask and social distancing within public transportation (Dzisi and Dei 2020)
- Optimally positioning the tables in a brewpub and umbrellas at beach, and family-group seat optimization in an amphitheater (Fischetti et al. 2021)
- Developing a seating distribution plan for finding the additional number of trains required in order to accommodate the passengers waiting for the next train within the safe social distance in NYC subway (Kamga et al. 2021)
- Analyzing the social vulnerability and built environment factors that affect COVID-19 cases (Kashem et al. 2021)
- Developing social distance compliant smart parking solutions that will help drivers to find an available parking space (Delot and Ilarri 2020).

In Table 3, we present studies reviewed within each problem domain with respect to countries. As expected, the USA and China are dominating almost all problem domains in terms of the number of studies. This table can be used as a quick reference and guide for the studies covered in our systematic review.

## 2.4 Decision problematic

In our systematic review, as another survey dimension, we categorize the reviewed articles with respect to the decision problematics as seen in Table 4 (RQ2). The decision problematic essentially defines the problem tackled in the study.

As Table 4 reveals, travel mode/choice estimation is one of the decision problematics that has received a great deal of interest from the researchers. Due to the perceived risk of COVID-19 pandemic, people have changed their travel mode and behavior in an effort to decrease contact with other individuals, which has led to a significant decrease in public transportation. Transportation system decision-makers needed reliable information regarding the change in travel mode/choices of individuals for efficient transportation planning. To that end, a majority of these studies explore the impact of COVID-19 pandemic on transportation

**Table 3** Studies within each problem domain with respect to countries

| Problem domain | Country | References |
|---|---|---|
| Effects of pandemic/epidemics on transportation | USA | Bian et al. (2021), Cavalcante da Silva et al. (2021), Cusack (2021), Du et al. (2021a), Hu et al. (2021b), Hu et al. (2021a), Jobe and Griffin (2021), Liu et al. (2021c), Monahan and Lamb (2021), Monmousseau et al. (2020), Morshed et al. (2021), Ozbilen et al. (2021a), Ozbilen et al. (2021b), Padmanabhan et al. (2021), Parker et al. (2021), Schneider et al. (2021), Shamshiripour et al. (2020), Teixeira and Lopes (2020), Truong (2021), Truong and Truong (2021), Wang et al. (2021c), Wang and Noland (2021), Wang et al. (2021a), Yao et al. (2021), Zhang and Fricker (2021) |
| | China | Chen et al. (2021c), Cui et al. (2021), Li et al. (2021b), Liu et al. (2021b), Lv et al. (2021), Sun et al. (2020), Sun et al. (2021c), Vo et al. (2021), Wu et al. (2021), Zhou et al. (2021a), Zhou et al. (2021b), Zhou et al. (2021c) |
| | Canada | Abu-Rayash and Dincer (2020), Fatmi (2020), Khaddar and Fatmi (2021), Loa et al. (2021), McKenzie and Adams (2020) |
| | India | Aaditya and Rahul (2021), Das et al. (2021), Pawar et al. (2021a) |
| | Pakistan | Abdullah et al. (2021), Haider and Hafeez (2021), Lee et al. (2021) |
| | Germany | Loske (2020), Reul et al. (2021) |
| | Iran | Sameni et al. (2021), Shaer et al. (2021) |
| | Israel | Elias and Zatmeh-Kanj (2021) |
| | UK | Li et al. (2021a) |
| | Australia | Mendolia et al. (2021) |
| | Brazil | Fumagalli et al. (2021) |
| | Ghana | Sogbe (2021) |

**Table 3** continued

| Problem domain | Country | References |
|---|---|---|
| | Greece | Michail and Melas (2020) |
| | Ireland | Crowley et al. (2021) |
| | Italy | Beria and Lunkar (2021) |
| | Japan | Hara and Yamaguchi (2021) |
| | Morocco | El Ouadi et al. (2021) |
| | Norway | Mueller (2021) |
| | Philippines | Hasselwander et al. (2021) |
| | Portugal | Teixeira et al. (2021) |
| | Singapore | Benita (2021) |
| | South Korea | Kim et al. (2021) |
| | Taiwan | Chang et al. (2021) |
| | Turkey | Shakibaei et al. (2021) |
| Logistics and delivery systems | China | Chen et al. (2020), Chen et al. (2021b), Choi (2020), Jiang et al. (2021), Liu et al. (2021a), Wu et al. (2020), Yang et al. (2021), Eriskin et al. (2022), Ala et al. (2022) |
| | USA | Figliozzi and Unmikrishnan (2021), Giunipero et al. (2021), Nagurney (2021), Rajendran and Harper (2021) |
| | India | Mondal and Roy (2021), Paul and Venkateswaran (2020), Srinivas and Marathe (2021) |
| | Iran | Goodarzian et al. (2021), Hosseini-Motlagh et al. (2021), Mosallanezhad et al. (2021), |

**Table 3** continued

| Problem domain | Country | References |
|---|---|---|
| | | Alinaghian and Goli (2017) |
| | Japan | Ishida (2020), Rashed et al. (2021) |
| | Austria | Kunovjanek and Wankmüller (2021), Wolfinger et al. (2021) |
| | Australia | Rahman et al. (2021) |
| | Canada | Simsek et al. (2021) |
| | France | El Baz and Ruel (2021) |
| | Haiti | Du et al. (2021b) |
| | Indonesia | Perdana et al. (2020) |
| | Mexico | Hernández-Pérez and Ponce-Ortega (2021) |
| | Norway | Sun et al. (2021a) |
| | Sierra Leone | Eyres et al. (2015) |
| | South Korea | Singgih (2020) |
| | Turkey | Tirkolaee et al. (2022) |
| | UK | Nikolopoulos et al. (2021) |
| | West Africa | Buyuktahtakin et al. (2018) |

**Table 3** continued

| Problem domain | Country | References |
|---|---|---|
| Effect of mobility on pandemic spread | China | An et al. (2021), Habib et al. (2021), Hua et al. (2021), Li et al. (2021c), Li and Ma (2021), Liu et al. (2021d), Lu et al. (2021), Sun et al. (2021b), Wei et al. (2020), Wei et al. (2021), Xue et al. (2021), Zhu and Guo (2021) |
|  | USA | Abulhassan and Davis (2021), Bhouri et al. (2021), Brinkman and Mangum (2021), Gaskin et al. (2021), Glaeser et al. (2020), Qian and Ukkusuri (2021), Tokey (2021), Vrabac et al. (2021), Wali and Frank (2021), Wang et al. (2021b) |
|  | Iran | Ahmadzadeh and Shams (2021), Lak et al. (2021), Motevalli-Taher and Paydar (2021) |
|  | India | Maji et al. (2020), Thombre and Agarwal (2021) |
|  | Canada | Gargoum and Gargoum (2021) |
|  | Denmark | Ghayvat et al. (2021) |
|  | Estonia | Goel and Sharma (2020) |
|  | Germany | Ding et al. (2021) |
|  | Indonesia | Pasaribu et al. (2021) |
|  | Italy | Merler and Ajelli (2010) |
|  | Latin America | Kephart et al. (2021) |
|  | Singapore | Mo et al. (2021) |

**Table 3** continued

| Problem domain | Country | References |
|---|---|---|
| Medical waste management and wastewater-based epidemiology | China | Chen et al. (2021a), Zhao et al. (2021) |
| | Iran | Govindan et al. (2021), Tirkolaee et al. (2021) |
| | USA | Cao and Francis (2021), Rallapalli et al. (2021) |
| | Germany | Burgos and Ivanov (2021) |
| | Singapore | Shah et al. (2021) |
| | Spain | Calle et al. (2021) |
| | Turkey | Eren and Tuzkaya (2021) |
| Vaccine planning models | USA | Enayati and Özaltın (2020), Luo et al. (2018), Madewell et al. (2021), Thakore et al. (2021) |
| | Bangladesh | Alam et al. (2021) |
| | China | Lin et al. (2021) |
| | Greece | Georgiadis and Georgiadis (2021) |
| | Iran | Rastegar et al. (2021) |
| | Malaysia | Albahri et al. (2021) |
| | Turkey | Çakır et al. (2021) |
| Social distancing models | USA | Allcott et al. (2020), Iio et al. (2021), Kamga et al. (2021), Kashem et al. (2021) |
| | Denmark | Fischetti et al. (2021) |
| | France | Delot and Ilarri (2020) |
| | Ghana | Dzisi and Dei (2020) |

systems both public and private, travel mode/behaviors of individuals, and their relationship with COVID-19 cases.

One of the main measures taken to reduce the spread of the pandemic is to decrease human mobility. Hence, almost all countries have taken measures such as lockdown, quarantine, and travel bans to decrease human mobility. Conversely, most of the people have practiced self-imposed restrictions that are shaped by the perceived risk of the pandemic. In this context, changes in population mobility in response to the COVID-19 pandemic have been explored within the decision problematics *population mobility estimation*, and *traffic density estimation*. Furthermore, the authors have studied on the prediction of domestic and international travel demand facing global disruptions, especially in air transportation networks. Some other researchers have conducted a *passenger sentiment-emotion analysis* to measure customer satisfaction based on large-scale Twitter data.

Another decision problematic addressed by the researchers is *spread modeling/case prediction*. The reviewed articles in this category aim to understand the spread pattern of the pandemic in relation to social connectivity and mobility, and to predict the expected number of COVID-19 cases in this regard. Some other studies examined the relationship between the concentration of SARS-CoV-2 virus in the wastewater and the number of COVID-19 cases. From the OR perspective, determining the optimal monitoring sites for SARS-CoV-2 surveillance, identifying target population clusters, and forecasting the number of COVID-19 infections have emerged as new problems considered under *wastewater-based epidemiology* decision problematic.

*Vaccine planning* is another decision problematic that the researchers tackle. From the OR perspective, this decision problematic addresses problems such as determining vaccination sites, allocation of vaccines to distribution centers, design of cold chain logistics, and determining the groups to be vaccinated.

The decision problematic *social distance optimization* focuses on problems such as optimal and safest arrangement of seats/individuals within a confined area, in particular, public transportation vehicles to minimize the overall risk of infection.

Pandemics often result in rapid depletion and insufficient supply of medical resources. Timely and rapid transportation of medical supplies, which may require special storage conditions, plays an important role in saving lives in pandemics/large-scale emergencies. Moreover, determining the quantity and location of demand for medical supply is of utmost importance for an efficient planning. Therefore, *medical center location*, *medical resources allocation*, *medical resource scheduling*, and *supply/medical vehicle routing* emerge as important decision problematics to be address to mitigate the effects of pandemic. To that end, problems such as transportation of medical supplies and related items to healthcare facilities, emergency services or between production facilities and population zones, locating the supply distribution centers for medical items and allocating inventories to these facilities, combined planning of location, transportation, inventory allocation, and routing problems have been studied by many researchers.

The amount of medical waste generated during the pandemic exceeded the regular waste handling capacity and yielded another decision problematic, i.e., *medical waste transportation-routing*. This decision problematic consists of problems such as locating and/or sizing of waste disposal sites and/or waste storage areas, determining optimal routes for medical waste collection vehicles, locating temporary treatment centers and/or transfer stations, determining the optimal number and routing of waste collection vehicles.

The COVID-19 pandemic posed new challenges to all kinds of logistics systems due to measures taken such as lockdown, travel bans and closure of borders, as well as fluctuations in demand for supplies. Having observed these new challenges, logistics companies had

to tailor their regular supply chain policies with respect to *new normal*. Hence, numerous studies have been conducted to address problems emerge within *logistics demand prediction* and *determining new supply chain policies* decision problematic, such as determining the design and routes for multi-mode transportation networks for same-day instant food delivery services, locating and sizing of regional distribution hubs, determining optimal transportation routes among the supply chain, route planning for unmanned transportation vehicles and assistant robots for food delivery, transportation of fresh agri-product emergency supplies, and combined multi-item packaging, vehicle assignment, delivery routing with split delivery.

## 2.5 Solution methods

This subsection analyzes the reviewed papers in terms of the methods used (RQ2). The solution methods employed in the reviewed papers can be clustered into 11 distinct groups as shown in Table 5. Conversely, it worths noting that 19 studies among the 167 reviewed papers employ more than one type of solution method.

*Data analysis* constitutes the biggest cluster with 70 studies. This cluster involves analyses such as descriptive statistics (Zhu and Guo 2021; Zhou et al. 2021c; Hu et al. 2021b), hypothesis testing (Wei et al. 2020; Yao et al. 2021; Chen et al. 2021c), survey analysis (Thombre and Agarwal 2021; Sogbe 2021), and correlation analysis (Glaeser et al. 2020; Li and Ma 2021). We observed that data analysis has played an important role in understanding the dynamics of the COVID-19 pandemic through analysis of large data sets. Among these studies, a large body of papers analyze the surveys conducted to understand the changes and patterns in people's travel behaviors and modes. Some others perform hypothesis testing to understand if there exists statistical difference between the pre-and-post COVID-19 era in terms of transportation.

*Mathematical Modeling* is the second largest cluster, accounting for 32 of the 167 reviewed papers. In particular, these studies employ mostly linear programming and integer/mixed integer programming models to optimize the objective of interest, such as medical/distribution center location optimization (Goodarzian et al. 2021; Perdana et al. 2020; Eriskin et al. 2022), resource allocation/distribution optimization (Du et al. 2021b; Mosallanezhad et al. 2021; Chen et al. 2020), and supply/medical vehicle routing optimization (Kunovjanek and Wankmüller 2021; Mondal and Roy 2021; Perdana et al. 2020; Wolfinger et al. 2021). It is remarkable that 16 of the 29 mathematical modeling studies address the *Logistics and delivery systems* problem domain.

*Simulation Modeling*, on the other hand, has been one of the methods we have come across to analyze virus spread and its impact on transportation systems. Our review of the literature revealed that simulation models are commonly used by scholars to assess the performance and behavior of systems involving uncertainty in epidemic/pandemic environments. Several well-known simulation modeling approaches, e.g., Agent-Based Simulation (ABS) modeling, metapopulation models, and system dynamics (sometimes called as the susceptible-infected-recovered (SIR) compartment models) have been used by planners in many real-world decision problems. Simulation models have the advantage of handling uncertainties associated with the disease spread structure and rate. Among them, ABS models are capable of modelling the spatio–temporal travel behavior of individual agents as well as government policies with a specific fidelity. They can also account for the heterogeneity of individuals in the population in terms of various features, such as age, sex, underlying conditions and can model the interactions of agents at micro-level. Metapopulation models, on the other hand, aim at modelling the interactions among various sub-populations. Since they

**Table 4** Decision problematic

| Decision problematic | References | Number of papers |
| --- | --- | --- |
| Travel mode/choice estimation | Aaditya and Rahul (2021), Abdullah et al. (2021), Bian et al. (2021), Brinkman and Mangum (2021), Chang et al. (2021), Crowley et al. (2021), Cusack (2021), Das et al. (2021), Elias and Zatmeh-Kanj (2021), El Ouadi et al. (2021), Hara and Yamaguchi (2021), Hu et al. (2021a), Hua et al. (2021), Jobe and Griffin (2021), Khaddar and Fatmi (2021), Kim et al. (2021), Liu et al. (2021b), Li et al. (2021c), Li et al. (2021a), Liu et al. (2021c), Loa et al. (2021), McKenzie and Adams (2020), Monahan and Lamb (2021), Ozbilen et al. (2021a), Ozbilen et al. (2021b), Padmanabhan et al. (2021), Parker et al. (2021), Pawar et al. (2021a), Rajendran and Harper (2021), Sameni et al. (2021), Shaer et al. (2021), Shakibaei et al. (2021), Shamshiripour et al. (2020), Sogbe (2021), Teixeira and Lopes (2020), Teixeira et al. (2021), Thombre and Agarwal (2021), Truong and Truong (2021), Vo et al. (2021), Wang and Noland (2021), Wang et al. (2021b), Zhang and Fricker (2021), Zhou et al. (2021b) | 43 |
| Population mobility estimation | Abu-Rayash and Dincer (2020), Benita (2021), Beria and Lunkar (2021), Fatmi (2020), Gargoum and Gargoum (2021), Ghayvat et al. (2021), Glaeser et al. (2020), Habib et al. (2021), Hasselwander et al. (2021), Hu et al. (2021b), Kephart et al. (2021), Lee et al. (2021), Liu et al. (2021d), Mendolia et al. (2021), Merler and Ajelli (2010), Qian and Ukkusuri (2021), Tokey (2021), Wang et al. (2021c) | 18 |
| Spread modeling/ case prediction | Ahmadzadeh and Shams (2021), Bhouri et al. (2021), Gaskin et al. (2021), Goel and Sharma (2020), Lak et al. (2021), Li and Ma (2021), Mo et al. (2021), Pasaribu et al. (2021), Sun et al. (2021c), Sun et al. (2021b), Vrabac et al. (2021), Wali and Frank (2021), Wei et al. (2020), Wei et al. (2021), Yao et al. (2021), Zhu and Guo (2021) | 16 |
| Travel demand prediction | An et al. (2021), Cui et al. (2021), Du et al. (2021a), Fumagalli et al. (2021), Li et al. (2021b), Maji et al. (2020), Mueller (2021), Reul et al. (2021), Sun et al. (2020), Truong (2021), Zhou et al. (2021c) | 11 |
| Vaccine planning | Çakır et al. (2021), Alam et al. (2021), Albahri et al. (2021), Enayati and Özaltın (2020), | 11 |

**Table 4** continued

| Decision problematic | References | Number of papers |
| --- | --- | --- |
| Social distance optimization | Georgiadis and Georgiadis (2021), Lin et al. (2021), Luo et al. (2018), Madewell et al. (2021), Rastegar et al. (2021), Sun et al. (2021a), Thakore et al. (2021) | 10 |
| Medical resource allocation | Abulhassan and Davis (2021), Allcott et al. (2020), Cavalcante da Silva et al. (2021), Delot and Ilarri (2020), Dzisi and Dei (2020), Fischetti et al. (2021), Iio et al. (2021), Kamga et al. (2021), Kashem et al. (2021), Schneider et al. (2021) | 10 |
| Traffic density estimation | Buyuktahtakin et al. (2018), Du et al. (2021b), El Baz and Ruel (2021), Eyres et al. (2015), Hosseini-Motlagh et al. (2021), Mosallanezhad et al. (2021), Nagurney (2021), Hernández-Pérez and Ponce-Ortega (2021), Rahman et al. (2021), Eriskin et al. (2022) | 9 |
| Supply/medical vehicle routing | Chen et al. (2021c), Ding et al. (2021), Loske (2020), Lu et al. (2021), Lv et al. (2021), Wang et al. (2021a), Wu et al. (2021), Xue et al. (2021), Zhou et al. (2021a) | 7 |
| Logistics demand prediction | Chen et al. (2020), Chen et al. (2021b), Jiang et al. (2021), Kunovjanek and Wankmüller (2021), Perdana et al. (2020), Simsek et al. (2021), Singgih (2020) | 6 |
| Waste-water based epidemiology | Ishida (2020), Burgos and Ivanov (2021), Choi (2020), Figliozzi and Unnikrishnan (2021), Michail and Melas (2020), Nikolopoulos et al. (2021) | 5 |
| Medical waste transportation-routing | Calle et al. (2021), Cao and Francis (2021), Haider and Hafeez (2021), Rallapalli et al. (2021), Shah et al. (2021) | 5 |
| Medical resource scheduling | Chen et al. (2021a), Eren and Tuzkaya (2021), Govindan et al. (2021), Tirkolaee et al. (2021), Zhao et al. (2021) | 5 |
| Supply chain policy determination | Liu et al. (2021a), Mondal and Roy (2021), Rashed et al. (2021), Wu et al. (2020), Ala et al. (2022) | 5 |
| Medical center location | Giunipero (2021), Paul and Venkateswaran (2020), Srinivas and Marathe (2021), Yang et al. (2021), Tirkolaee et al. (2022) | 4 |
| Passenger sentiment- emotion analysis | Goodarzian et al. (2021), Motevalli-Taher and Paydar (2021), Wolfinger et al. (2021), Alinaghian and Goli (2017), Monmousseau et al. (2020), Morshed et al. (2021) | 2 |
| Total | | 167 |

are usually scaled up to global scale models, they run at higher speeds at the cost of lower model resolution. System dynamics are based on feedback systems theory and are used to understand the behavior of dynamic systems through models of differential equations. They model the processes by using stocks, flows between these stocks and information related to these flows (Borshchev and Filippov 2004). Compartment models, such as the SIR (Susceptible, Infectious, or Recovered) models also use system dynamics approach. SIR models, first developed by Kermack and McKendrick (1927) categorize the population into multiple compartments with different labels. Especially during the COVID-19 pandemic, different extensions on the SIR models such as the SEIR (Susceptible-Exposed-Infectious-Recovered) (Qian and Ukkusuri 2021), SEIHRD (Susceptible, Exposed, Infected, Hospitalized, Recovered, Dead) models (An et al. 2021) have been proposed and successfully used to model the disease spread patterns (Karatas et al. 2022b). Some examples include, evaluating the impact of international travel reductions and restrictions on pandemic (Sun et al. 2021b; Ding et al. 2021), estimating the spreading parameters and future forecasts of COVID-19 spread (Vrabac et al. 2021; Qian and Ukkusuri 2021; Bhouri et al. 2021; Goel and Sharma 2020), demonstrating the dynamics of epidemic spreading through public transit network (Mo et al. 2021; Du et al. 2021a; Cui et al. 2021), impact of the epidemic and transmission in households, schools, workplaces and in the general population (Merler and Ajelli 2010; Reul et al. 2021), customer demand and supply strategy during COVID-19 pandemic (Rahman et al. 2021; Sun et al. 2021a). The studies mainly provide valuable solutions by providing information about the spread of dynamics of infectious diseases and future forecasts of COVID-19 spread.

*Regression Analysis* is mostly used in the 'Effects of pandemic/epidemics on transportation' and 'Effect of mobility on pandemic spread' (17 of the 21 reviewed studies) problem domains to estimate the relationship between COVID-19 cases and death rates and patterns of disease spread (Gaskin et al. 2021; Lak et al. 2021), to analyze linkage between COVID-19 and transportation mobility (Habib et al. 2021; Liu et al. 2021d; Lu et al. 2021; Kim et al. 2021), to examine travel behavior, population mobility and its relationship with COVID-19 cases (Brinkman and Mangum 2021; Kephart et al. 2021; Zhou et al. 2021b; Padmanabhan et al. 2021). According to the authors, to reduce the health risk posed by COVID-19, people should travel less, shorten trip distances and duration, visit fewer destinations and avoid crowded or shared spaces. Tokey (2021) and Lak et al. (2021) used geographically weighted regression models to formalize the relationship between mobility and social distancing with disease spread. Kephart et al. (2021) implemented a binomial regression for a time-series analysis to measure the decrease of new cases in Latin American cities with the reduce population mobility at the sub-city level. Similarly, Gaskin et al. (2021) used negative binomial regression to determine the associations between mortality death rate and proximity to and size of train stations, airports, and other public transportation stations.

Similarly, *Forecasting and Time-series Analysis* is used in 8 studies. 7 of these studies offer solutions to the problem domains of the 'Effects of pandemic/epidemics on transportation' and 'Effect of mobility on pandemic spread' such as changes in mobility behavior before and during the COVID-19 lockdown (Hasselwander et al. 2021; Gargoum and Gargoum 2021; Liu et al. 2021c), forecasting the growth of the pandemic and modeling the transmission of virus (Nikolopoulos et al. 2021; Pasaribu et al. 2021). The authors point out that forecasting the reliability of the proposed models largely depends on the length of the time series. A time series is a set of observations obtained with regular intervals for any activity at different time and helps to forecast the data with higher accuracy (Hanif et al. 2022). For this reason, it is of great significance to evaluate the model in a long time frame in order to make more accurate decisions in terms of forecasting performance. *Trend analysis* and *change point analysis* are some other statistical techniques that are used to model and monitor the pandemic spreads

behavior of time series data. Gargoum and Gargoum (2021) studied the relationship between the timing of mobility restrictions and its impact on public health by implementing a change point analysis for 10 different countries. Highlighting the importance of taking early action, their results revealed that countries which took relatively early lockdown actions had the chance to operate at a higher level of mobility (approximately 40% of normal activity) with less mortality and disease spread rates during the lockdown. Pasaribu et al. (2021) used a time series model to capture the pattern of daily cases increase in Java Island, Indonesia, and one more time highlighted the importance of rapid testing strategies to alleviate the effect of pandemics. Truong and Truong (2021) implemented a time' series model via the Autoregressive Moving Average (ARIMA) method and trend analysis to predict future cases and deaths with respect to the daily trip trends of the population by distance. Their analysis revealed that there exists a closed-loop scenario, in which the travel behavior of the residents dynamically changes according to their perception of COVID-19 risk, which further contributes to the disease spread without an end.

*Multi criteria decision making* (MCDM) methods usually address the 'logistics and delivery systems' and 'vaccine planning systems' problem domains for supply chain and vaccine distribution policy determination. Some prominent example areas include improving the vaccine supply chain performance (Lin et al. 2021), vehicle assignment for effective COVID-19 vaccine distribution (Sun et al. 2021a; Alam et al. 2021), vehicle routing strategy for fresh agri-product supply (Jiang et al. 2021), optimum number of COVID-19 temporary vaccination clinics (Çakır et al. 2021). The studies balance the conflict between time and resources under the demand uncertainty.

*Deep learning* is used to forecast the number of COVID-19 cases and growth rates (Bhouri et al. 2021; Nikolopoulos et al. 2021), to analyze the impacts of COVID-19 on the transportation network usage (Yao et al. 2021; Wu et al. 2021) and to estimate the number of emergency ambulance dispatches during a state of emergency (Rashed et al. 2021).

There also exist several studies that applied *Machine Learning* approaches for the travel mode/choice analysis. For instance, Loa et al. (2021) implemented a Latent Class Cluster Analysis (LCAA) where they segmented travelers into six distinct clusters, namely, strict drivers, pedestrians/transit users, transit users, private vehicle/transit users, mobility-on-demand users/cyclists, and multimodals based on sociodemographic features of population. LCAA is a variant of the Cluster Analysis which accounts for measurement errors by applying a probabilistic approach. In another interesting study, Ozbilen et al. (2021b) explored the relationship between information technology usage, in particular telework and online shopping, and the time spent using different transportation modes during the pandemic. The authors utilized Regression Analysis to model the pertaining relationship while PCA was used to derive fundamental factors explaining this relationship. In a similar study, Teixeira et al. (2021) investigated the factors behind bike-sharing usage amid COVID-19 pandemic. They implemented a Factor Analysis and applied PCA to reduce 19 potential factors into a representative set. To determine the most important motivating factors, the authors implemented the Analysis of Variance (ANOVA) and hypothesis testing.

On another hand, *clustering* methods are presented to analyze the changes in daily human activities (Liu et al. 2021b), the temporal patterns of visits to health care access (Wang et al. 2021c) and the impact of pandemic-related countries' policies (McKenzie and Adams 2020; Loa et al. 2021). For example, *bayesian analysis* is proposed to identify targeted population clusters and optimized locations for implementation of wastewater-based epidemiology to detect COVID-19 (Rallapalli et al. 2021) and to analyze the impact of the COVID-19 epidemic on transportation systems (Bian et al. 2021; Zhang and Fricker 2021). As another commonly used approach, *neural networks* are used to tackle deriving useful information related to

mobility and pandemic dynamics. For example, (Truong 2021) uses neural networks to predict domestic and international air travel. (Lu et al. 2021), on the other hand, determines the relationship between the number of COVID-19 cases and a related explanatory variable through a transportation network. Finally, *reinforcement learning* method gives a solution for dynamic travel ban policy determination under the pandemic (An et al. 2021) and scheduling the real-time emergency production tasks (Wu et al. 2020).

Results of the analysis according to which methods are the most commonly used in the decision problematic are also presented in Table 6. It is worth to note that *data analysis* is mostly method used in travel mode/choice analysis and spread modeling/case prediction decision problematics.

To sum up, data-driven techniques and data analytics have the potential to improve transportation and location planning processes for better decision making. As also indicated in (Karatas et al. 2022a), our review showed that several researchers implemented holistic approaches that tackle novel healthcare system frameworks by incorporating data-driven concepts successfully. Substantial work has been done on using data analytics during pandemic in transportation and location planning and management. In Table 7, problem domains are divided into six areas, each of which is discussed in terms of used solution methods. The table reveals that the majority of investigated work focuses on data analysis and mathematical modeling, which constitutes approximately 54% of papers included in our review.

## 3 Mobility/transportation data collecting streams during pandemic/epidemic

Understanding how mobility changes under the pandemic/epidemic and the relationship between human mobility and the spread of the pandemic/epidemic is important for location and transportation problems. Keeping in mind the "Garbage in, garbage out" principle, OR studies pertaining to location and transportation problems require up-to-date and reliable data for efficient analysis and decision-making support.

As a sudden and unexpected health emergency, the recent COVID-19 pandemic has raised worldwide attention for rapid and reliable data sharing Liu et al. (2021c). Various global data sets such as confirmed cases, deaths, recoveries, and mobility of the public/individuals have been made available for researchers. Multi-source and multi-faceted characteristics of transportation data have enabled researchers to aggregate data from various sources. In particular, with the growth of the Global Positioning System (GPS) equipped mobile devices and relevant applications, a large amount of spatio–temporal mobility data have become available for transportation research. These raw data obtained from mobile devices have also been processed to generate new types of data set for specific purposes Hu et al. (2021c).

The way mobility/transportation data collected during the COVID-19 pandemic can be classified under two pillars: *active* and *passive* data collection. In active data collection, the researcher actively collects the required data in the context of the research. In passive data collection, conversely, the data are collected continuously as part of the daily routine of individuals such as smart card transactions, mobile applications, and airline bookings. It is evident that abundant data can be collected via passive data collection while data mining techniques are required to elicit relevant data for the pandemic research since these data are not collected aiming at a particular research question. We have observed through our review of the literature that recent research related to COVID-19 has mainly used passively collected data.

**Table 5** Methods used

| Methods used | References | Number of papers |
|---|---|---|
| Data Analysis | Ishida (2020), Aaditya and Rahul (2021), Abdullah et al. (2021), Abulhassan and Davis (2021), Abu-Rayash and Dincer (2020), Allcott et al. (2020), Benita (2021), Beria and Lunkar (2021), Chang et al. (2021), Chen et al. (2021a), Chen et al. (2021c), Crowley et al. (2021), Cusack (2021), Das et al. (2021), Dzisi and Dei (2020), El Baz and Ruel (2021), Elias and Zatmeh-Kanj (2021), El Ouadi et al. (2021), Eyres et al. (2015), Fatmi (2020), Figliozzi and Unnikrishnan (2021), Gaskin et al. (2021), Giunipero et al. (2021), Glaeser et al. (2020), Haider and Hafeez (2021), Hara and Yamaguchi (2021), Hu et al. (2021b), Hu et al. (2021a), Hua et al. (2021), Iio et al. (2021), Jobe and Griffin (2021), Kashem et al. (2021), Khaddar and Fatmi (2021), Lak et al. (2021), Lee et al. (2021), Li et al. (2021b), Li et al. (2021a), Li and Ma (2021), Loa et al. (2021), Madewell et al. (2021), Mendolia et al. (2021), Monahan and Lamb (2021), Morshed et al. (2021), Mueller (2021), Ozbilen et al. (2021a), Ozbilen et al. (2021b), Padmanabhan et al. (2021), Parker et al. (2021), Pasaribu et al. (2021), Pawar et al. (2021a), Sameni et al. (2021), Schneider et al. (2021), Shaer et al. (2021), Shah et al. (2021), Shakibaei et al. (2021), Shamshiripour et al. (2020), Sogbe (2021), Srinivas and Marathe (2021), Sun et al. (2020), Sun et al. (2021c), Teixeira and Lopes (2020), Teixeira et al. (2021), Thombre and Agarwal (2021), Wali and Frank (2021), Wei et al. (2020), Xue et al. (2021), Yao et al. (2021), Zhou et al. (2021a), Zhou et al. (2021c), Zhu and Guo (2021) | 70 |

**Table 5** continued

| Methods used | References | Number of papers |
|---|---|---|
| Mathematical Modeling | Bian et al. (2021), Buyuktahtakin et al. (2018), Calle et al. (2021), Chen et al. (2020), Chen et al. (2021b), Du et al. (2021b), Eriskin et al. (2022), Enayati and Özaltın (2020), Eren and Tuzkaya (2021), Fischetti et al. (2021), Georgiadis and Georgiadis (2021), Goodarzian et al. (2021), Govindan et al. (2021), Hosseini-Motlagh et al. (2021), Kamga et al. (2021), Kunovjanek and Wankmüller (2021), Liu et al. (2021a), Mondal and Roy (2021), Mosallanezhad et al. (2021), Motevalli-Taher and Paydar (2021), Nagurney (2021), Perdana et al. (2020), Hernández-Pérez and Ponce-Ortega (2021), Rastegar et al. (2021), Singgih (2020), Tirkolaee et al. (2021), Vo et al. (2021), Wolfinger et al. (2021), Zhao et al. (2021), Tirkolaee et al. (2022), Ala et al. (2022), Alinaghian and Goli (2017) | 32 |
| Simulation modeling | Ahmadzadeh and Shams (2021), Bhouri et al. (2021), Burgos and Ivanov (2021), Cui et al. (2021), Ding et al. (2021), Du et al. (2021a), Goel and Sharma (2020), Luo et al. (2018), Maji et al. (2020), Merler and Ajelli (2010), Mo et al. (2021), Qian and Ukkusuri (2021), Rahman et al. (2021), Rajendran and Harper (2021), Reul et al. (2021), Simsek et al. (2021), Sun et al. (2021b), Sun et al. (2021a), Vrabac et al. (2021), Wang et al. (2021a), Wang et al. (2021b), Wei et al. (2021) | 22 |

**Table 5** continued

| Methods used | References | Number of papers |
|---|---|---|
| Regression Analysis | Bian et al. (2021), Brinkman and Mangum (2021), Cao and Francis (2021), Fumagalli et al. (2021), Gaskin et al. (2021), Habib et al. (2021), Kephart et al. (2021), Kim et al. (2021), Lak et al. (2021), Li et al. (2021c), Li et al. (2021a), Liu et al. (2021d), Loske (2020), Lu et al. (2021), Michail and Melas (2020), Padmanabhan et al. (2021), Paul and Venkateswaran (2020), Thakore et al. (2021), Tokey (2021), Yang et al. (2021), Zhou et al. (2021b) | 21 |
| Multi criteria decision making | Çakır et al. (2021), Alam et al. (2021), Albahri et al. (2021), An et al. (2021), Avanzi and Zerjav (2020), Choi (2020), Ding et al. (2021), Ghayvat et al. (2021), Jiang et al. (2021), Lin et al. (2021), Monmousseau et al. (2020), Rajendran and Harper (2021), Reul et al. (2021), Sun et al. (2021a) | 14 |
| Forecasting and time-series analysis | Cavalcante da Silva et al. (2021), Gargoum and Gargoum (2021), Hasselwander et al. (2021), Liu et al. (2021c), Nikolopoulos et al. (2021), Pasaribu et al. (2021), Truong and Truong (2021), Wang and Noland (2021) | 8 |
| Deep learning | Bhouri et al. (2021), Lv et al. (2021), Nikolopoulos et al. (2021), Rashed et al. (2021), Wu et al. (2021), Yao et al. (2021) | 6 |
| Clustering | Delot and Ilarri (2020), Liu et al. (2021b), Loa et al. (2021), McKenzie and Adams (2020), Wang et al. (2021c) | 5 |
| Bayesian analysis | Bian et al. (2021), Rallapalli et al. (2021), Zhang and Fricker (2021) | 3 |
| Neural Networks | Lu et al. (2021), Truong (2021), Wu et al. (2020) | 3 |
| Reinforcement learning | An et al. (2021), Wu et al. (2020) | 2 |
| **Total** | | **186** |

**Table 6** Decision problematic w.r.t. method used

| Decision problematic | Bayesian analysis | Clustering | Data analysis | Deep learning | Forecasting and time-series analysis | Mathematical modeling | Multi criteria decision making | Neural networks | Regression analysis | Reinforcement learning | Simulation modeling |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Logistics demand prediction | – | – | 2 | 1 | 1 | – | 1 | – | 1 | – | 1 |
| Medical center location | – | – | – | – | – | 4 | – | – | – | – | – |
| Medical resource allocation | – | – | 2 | – | – | 7 | – | – | – | – | 1 |
| Medical resource scheduling | – | – | – | 1 | – | 3 | – | – | – | – | – |

**Table 6** continued

| Decision problematic | Bayesian analysis | Clustering | Data analysis | Deep learning | Forecasting and time-series analysis | Mathematical modeling | Multi criteria decision making | Neural networks | Regression analysis | Reinforcement learning | Simulation modeling |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Medical waste transportation-routing | – | – | 1 | – | – | 4 | – | – | – | – | – |
| Passenger sentiment-emotion analysis | – | – | 1 | – | – | – | 1 | – | – | – | – |
| Population mobility estimation | – | 1 | 8 | – | 2 | – | 1 | – | 4 | – | 2 |
| Social distance optimization | – | 1 | 6 | – | 1 | 2 | – | – | – | – | – |
| Spread modeling/case prediction | – | – | 9 | 2 | 1 | – | – | – | 2 | – | 7 |

**Table 6** continued

| Decision problematic | Bayesian analysis | Clustering | Data analysis | Deep learning | Forecasting and time-series analysis | Mathematical modeling | Multi criteria decision making | Neural networks | Regression analysis | Reinforcement learning | Simulation modeling |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Supply chain policy determination | – | – | 2 | – | – | 1 | – | – | 2 | – | – |
| Supply/medical vehicle routing | – | – | – | – | – | 5 | 1 | 1 | – | 1 | 1 |
| Traffic density estimation | – | – | 3 | 2 | – | – | 1 | 1 | 2 | – | 2 |
| Travel demand prediction | – | – | 4 | – | – | – | 3 | 1 | 1 | 1 | 4 |
| Travel mode/choice analysis | 2 | 3 | 29 | – | 3 | 2 | 1 | – | 7 | – | 2 |
| Vaccine planning | – | – | 1 | – | – | 3 | 5 | – | 1 | – | 2 |
| Waste-water based epidomology | 1 | – | 2 | – | – | 1 | – | – | 1 | – | – |
| Total | 3 | 5 | 70 | 6 | 8 | 32 | 14 | 3 | 21 | 2 | 22 |

**Table 7** Problem domains with respect to solution methods

| Problem domain | Domain outlook | Solution methods | Number of papers |
|---|---|---|---|
| Effects of pandemic on transportation | This problem domain primarily investigates the impact of pandemics on all aspects of transportation such as travel behavior/modes, tourism, migration, and travel types. In particular, studies in this domain aim at predicting travel demand/mobility and travel mode/choice of people in an effort to provide efficient decision support to the transportation decision makers | Data Analysis | 44 |
| | | Forecasting and time-series analysis | 5 |
| | | Regression Analysis | 5 |
| | | Simulation modeling | 4 |
| | | Clustering | 3 |
| | | Deep learning | 3 |
| | | Bayesian analysis | 2 |
| | | Mathematical Modeling | 1 |
| | | MCDM | 1 |
| | | Neural Networks | 1 |

**Table 7** continued

| Problem domain | Domain outlook | Solution methods | Number of papers |
|---|---|---|---|
| Logistics and delivery systems | Considering the long-term disruption existence, high uncertainty, and the ripple effect of the pandemics, studies in this domain aim at developing resilience strategies to overcome problems that stem from the uncertainty in demand and production, additional hygiene measures, panic buying, and fluctuations in purchasing patterns. Supply chain operation strategies are investigated to address emerging problems related to pandemic with OR perspective | Mathematical Modeling | 19 |
| | | Data analysis | 6 |
| | | Simulation modeling | 4 |
| | | MCDM | 2 |
| | | Regression analysis | 2 |
| | | Deep learning | 1 |
| | | Forecasting and time-series analysis | 1 |
| | | Reinforcement learning | 1 |

**Table 7** continued

| Problem domain | Domain outlook | Solution methods | Number of papers |
|---|---|---|---|
| Effect of mobility on pandemic spread | Studies in this problem domain investigate the relationship between pandemics and mobility from the flip side of the coin: What is the impact or relevance of travel habits and mobility density of the population to the pandemic/epidemic spread? In this regard, studies pertaining to this research domain primarily employ both deterministic and stochastic simulation models to understand and model the relationship between human mobility and pandemic spread | Data analysis | 11 |
| | | Simulation modeling | 11 |
| | | Regression Analysis | 7 |
| | | Deep learning | 1 |
| | | Forecasting and time-series analysis | 1 |
| | | Mathematical Modeling | 1 |
| | | MCDM | 1 |
| | | Neural Networks | 1 |
| | | Reinforcement learning | 1 |

**Table 7** continued

| Problem domain | Domain outlook | Solution methods | Number of papers |
|---|---|---|---|
| Medical waste management and wastewater-based epidemiology | To deal with growing amount of medical waste, studies in this problem domain propose approaches for determining the location and size of storage areas and routing waste collection vehicles in a cost-efficient way. Moreover, finding optimal locations for biosensors used to monitor SARS Cov-2 concentration in the wastewater network and modeling the relationship between SARS Cov-2 concentration and COVID-19 cases falls in this category | Mathematical Modeling | 5 |
| | | Data analysis | 2 |
| | | Bayesian analysis | 1 |
| | | Regression Analysis | 1 |
| | | Simulation modeling | 1 |

**Table 7** continued

| Problem domain | Domain outlook | Solution methods | Number of papers |
|---|---|---|---|
| Vaccine planning models | Studies in this problem domain aim at developing various location and routing optimization models for supply chain operations to meet increasing demand for vaccines, medicines, and test kits. Decision support analytics are also provided for mass vaccination and immunization planning. | MCDM | 4 |
| | | Mathematical Modeling | 3 |
| | | Data analysis | 1 |
| | | Regression analysis | 1 |
| | | Simulation modeling | 1 |

**Table 7** continued

| Problem domain | Domain outlook | Solution methods | Number of papers |
| --- | --- | --- | --- |
| Social distancing models | This problem domain aims at determining the minimum social distance among people to reduce the risk of contracting the disease. In this regard, analytical solutions for the following questions are developed: How to place items such as tables and seats in restaurants, cafes, offices under safety constraints? How do social distancing rules affect the spread of the virus? What is the relationship between population density and public policies? | Data Analysis<br>Mathematical modeling<br>Clustering | 4<br>2<br>1 |

Through passive data collection, a growing volume of mobility/transportation data has been collected, and big data applications have helped generating new types of data with advanced algorithms, network coverage, and large-scale computing infrastructures (Hu et al. 2021c). These massive data are usually collected in raw formats and characterized with the typical five challenging *V*s: *volume*, *velocity*, *variety*, *veracity*, and *value* (Gudivada et al. 2015). Additionally, health big-data analytics played an important role in enhancing the decision making processes (Zheng et al. 2020). Therefore, COVID-19 related transportation and location research has revealed the need for high-performance data storage, processing, and the ability to extract relevant and valuable information from these data while accounting for the five aforementioned *V*s.

From the transportation and location viewpoint, four major data collection streams have become prominent for COVID-19 related OR studies Hu et al. (2021c): (*i*) Public transportation systems, (*ii*) surveys, (*iii*) mobile phone applications, (*iv*) mobile network operators. In Table 8, we categorize the reviewed articles in terms of the data collection streams details of which will be provided in the following subsections (RQ3).

## 3.1 Public transportation systems

Intelligent solutions for public transportation systems such as smart travel cards have become prevalent recently with the rapid advancements in computer science and intelligent systems. These solutions not only provide real-time and accurate transportation data but also enable storing large amounts of raw data containing valuable information for the analysis (Ali et al. 2016). These data are collected passively via the daily routine of transportation operations, without requiring any further effort to obtain them. For instance, in Seoul, approximately 2.2 GB data are generated daily through smart travel card transactions (Ali et al. 2016). Hence, even though their main purpose is to withdraw fares from passengers, smart travel cards enable gathering a large amount of transportation data that can be used for providing guidance to decision-makers particularly during emergencies such as pandemics/epidemics. Numerous researchers have utilized data generated by smart travel card transactions for their studies pertaining to the recent COVID-19 pandemic (Zhou et al. 2021b; Mützel and Scheiner 2021; Almlöf et al. 2021). Since there exists abundant travel data of various types, data mining techniques are usually utilized to infer meaningful data.

Other than smart travel cards, transportation data are made available by bus, train, ferry, metro, and airline companies, as well. These data generally comprises of aggregated human mobility data such as scheduled timetables and actual aggregated travel records. Another valuable data source is bike-sharing data provided by bike-sharing operators. During the COVID-19 pandemic, bike-sharing data have been analyzed by many researchers to understand how bike-sharing usage changes spatio–temporally and whether bike-sharing is a more resilient option compared to other modes of transportation (Hu et al. 2021a; Bian et al. 2021; Wang and Noland 2021).

## 3.2 Surveys

Surveys are another way to obtain information about the behavior of people in mobility and transportation choices. They involve customized questions for elucidating the relevant information. With the prevalence of the Internet, surveys are usually applied through web-based platforms. Surveys have been heavily used to obtain mobility choice and travel mode elucidation of individuals in COVID-19 related transportation research (Cusack 2021; Zhou

**Table 8** The number of with respect to data collection streams

| Data collection streams | References | Number of papers |
|---|---|---|
| Public transportation systems | Abu-Rayash and Dincer (2020), Bian et al. (2021), Chang et al. (2021), Cui et al. (2021), Ding et al. (2021) Fumagalli et al. (2021), Gaskin et al. (2021), Hu et al. (2021a), Hua et al. (2021),Kim et al. (2021), Li et al. (2021b), Li et al. (2021a), Li and Ma (2021), Lu et al. (2021), Luo et al. (2018),Merler and Ajelli (2010), Mueller (2021), Padmanabhan et al. (2021), Pasaribu et al. (2021), Qian and Ukkusuri (2021), Rajendran and Harper (2021),Sun et al. (2020), Sun et al. (2021c), Sun et al. (2021b), Teixeira and Lopes (2020), Truong (2021), Truong and Truong (2021),Vo et al. (2021), Vrabac et al. (2021), Wang and Noland (2021), Wang et al. (2021a), Wang et al. (2021b), Wei et al. (2020),Xue et al. (2021), Yao et al. (2021), Zhang and Fricker (2021), Zhou et al. (2021a), Zhou et al. (2021b), Zhou et al. (2021c), Zhu and Guo (2021) | 40 |

**Table 8** continued

| Data collection streams | References | Number of papers |
|---|---|---|
| Survey | Aaditya and Rahul (2021), Abdullah et al. (2021), Alam et al. (2021), Chen et al. (2021a), Chen et al. (2021c), Cusack (2021), Das et al. (2021), Dzisi and Dei (2020), El Baz and Ruel (2021), Elias and Zatmeh-Kanj (2021), Fatmi (2020), Figliozzi and Unnikrishnan (2021), Giunipero et al. (2021), Jobe and Griffin (2021), Kamga et al. (2021),Kashem et al. (2021), Khaddar and Fatmi (2021), Lee et al. (2021), Liu et al. (2021c), Loa et al. (2021), Luo et al. (2018),Monahan and Lamb (2021), Ozbilen et al. (2021a), Ozbilen et al. (2021b), Parker et al. (2021), Pawar et al. (2021a), Reul et al. (2021),Sameni et al. (2021), Shaer et al. (2021), Shakibaei et al. (2021), Shamshiripour et al. (2020), Sogbe (2021), Teixeira et al. (2021), Thakore et al. (2021), Thombre and Agarwal (2021), Wang et al. (2021a), Zhou et al. (2021b) | 37 |
| Mobile phone applications | Abu-Rayash and Dincer (2020), Allcott et al. (2020), Beria and Lunkar (2021), Bhouri et al. (2021), Cavalcante da Silva et al. (2021), Du et al. (2021a), Gargoum and Gargoum (2021), Glaeser et al. (2020), Habib et al. (2021), Hasselwander et al. (2021), Iio et al. (2021), Kashem et al. (2021), Kephart et al. (2021), Liu et al. (2021d), Liu et al. (2021c), Lv et al. (2021), Mendolia et al. (2021), Monmousseau et al. (2020), Morshed et al. (2021), Simsek et al. (2021), Tokey (2021), Wang et al. (2021c), Wei et al. (2021) | 23 |
| Mobile network operators | An et al. (2021), Brinkman and Mangum (2021), Eyres et al. (2015), Ghayvat et al. (2021), Hara and Yamaguchi (2021), Hu et al. (2021b), Liu et al. (2021b), Li et al. (2021c), McKenzie and Adams (2020),Mo et al. (2021), Parker et al. (2021), Rashed et al. (2021) | 12 |
| **Total** | | **112** |

et al. 2021b; Liu et al. 2021c; Loa et al. 2021; Elias and Zatmeh-Kanj 2021; Pawar et al. 2021b; Aaditya and Rahul 2021; Parker et al. 2021; Ozbilen et al. 2021b; Teixeira et al. 2021; Reul et al. 2021; Das et al. 2021; Shaer et al. 2021; Chen et al. 2021c; Sameni et al. 2021).

Survey data are not open-source and require additional effort to obtain; however, they provide important contextual information such as purpose of travel, exact destinations, and demographic profiles which can not be obtained by passive data collection techniques (Hu et al. 2021c). In general, studies that employ surveys and questionnaires for transportation-related data analytics deal with *ranking* and *choice* decision-making problematics. In *ranking* decision-problematic, alternatives are rank-ordered from the most preferred to the least preferred while within the *choice* decision-making problematic, the best or limited set of best alternatives are identified (Erişkin 2021). Within the context of *choice* decision-making problematic, the researchers aimed to explain the relationship between people's travel mode choices and other explanatory factors such as demographics (i.e., monthly income, age, gender), distance to public transport services, number of confirmed cases, and vehicle ownership with statistical models. Conversely, similar statistical relationship between explanatory variables and rank-ordered travel mode alternatives (i.e., bus, bike-sharing, train, walking) has been explored by researchers within the *ranking* decision-making problematic. There are also studies that investigate if there exists travel mode preference change between pre-pandemic and pandemic periods (Loa et al. 2021).

In our review, we have observed that mostly parametric statistical models such as logistic regression (Das et al. 2021; Pawar et al. 2021b; Parker et al. 2021; Reul et al. 2021), tobit regression (Ozbilen et al. 2021b), structural equation modeling (Elias and Zatmeh-Kanj 2021), and ANOVA (Teixeira et al. 2021) have been used to explain the aforementioned relationship. Although parametric statistical models are convenient because they provide easy-to-understand and interpretable models, nonparametric statistical models could achieve better results due to their ability to handle complex data structures and generalization ability (Erişkin and Köksal 2016). Moreover, most of the surveys introduced in the reviewed papers are not structured to elicit as much and efficient information as possible from the respondents. To address this issue, we envision that design of experiments techniques can be utilized to design efficient surveys and obtain significant statistical models.

Different than the aforementioned data collection streams, surveys can be considered as an active data collection technique where the data is collected actively by getting the consent and active participation of the respondent. Usually surveys are conducted via web-based platforms, hence, survey respondents are more likely to be younger and belong to middle/upper income households. This is the key limitation of the survey in terms of achieving an even representability of the target population.

### 3.3 Mobile phone applications

Mobile devices have many applications installed either by default or by the user. With the prevalence of mobile devices, various types of data regarding users' activities have been collected by the installed applications. Since most of the mobile devices are fitted with GPS, it has been possible to obtain real-time spatio–temporal data of individuals. These data contain valuable information regarding an individual's daily mobility behaviors. For instance, navigation applications such as Google Maps and Apple Maps record real-time GPS locations while providing services to users. Recorded information is a useful means for measuring access frequency to the Points of Interest (POI) such as hospitals, shopping centers, public facilities, etc (Hu et al. 2021c).

With the emerge of the COVID-19 pandemic, Google released Community Mobility Reports as PDF files on 2 April 2020, which provide aggregated mobility information from users who actively turned on their location history settings. The main purpose of these reports is to give insights for identifying the types of places people visit and how people's travel behavior has changed during the early stages of the pandemic (Chan et al. 2020). The reports include anonymized data that give the trends of visits to high-level categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential (Aktay et al. 2020). Similar mobility reports have also been available for researchers by the Apple (Apple Mobility Trend Reports), as well. In this regard, several studies have used these mobility reports for transportation research pertaining to COVID-19 (Liu et al. 2021d; Hasselwander et al. 2021; Mendolia et al. 2021; Liu et al. 2021c).

Apart from navigation applications, social media platforms also offer valuable information regarding the mobility behaviors of individuals during the pandemics/epidemics. Among those, for instance, Twitter is one of the largest social media platforms which allows users to share their opinions and feelings regarding various topics. Twitter contains two kinds of data: (*i*) streams of tweets, and (*ii*) location data recorded by the application. This content has made Twitter a valuable source of information for transportation planning, traffic monitoring, and traffic information dissemination, as well as understanding the mobility behavior trends of users during pandemics/epidemics (Liu et al. 2021c).

As a novel study exploiting social media data, Morshed et al. (2021) aimed at extracting ride-hailing service users' behavioral patterns via their Twitter messages to better understand the social and economic impact of COVID-19 pandemic on shared mobility. Based on large-scale Twitter data, a sentiment-emotion analysis was implemented, which classifies tweets in layers to elucidate the verdict regarding the experience.

### 3.4 Mobile network operators

With the ubiquity of GPS enabled mobile devices, particularly mobile phones, travel and mobility data collection have dramatically changed and become flexible during the last two decades. Moreover, variety of sensors fitted in these devices have enabled collecting various types of behavioral data in addition to location data. These data are collected passively without any effort and with higher penetration and temporal resolution thanks to the GPS location data and cell tower information that are aggregated for fine-tuned tracking (Hu et al. 2021b). Mobile network operators collect an abundant amount of location data, which are particularly useful for traffic congestion monitoring, public security, and urban planning. Mobile network operator enabled data have also paved the way for a new kind of statistics in Japan, in particular *Mobile Spatial Statistics*, which is defined as population statistics for estimating the actual population in areas throughout Japan (Hara and Yamaguchi 2021).

With the emerge of COVID-19 pandemic, some of the mobile network operators unlocked access to mobility data of users and enabled limited access. Since these data contain personal information, generally aggregated data have been made available for researchers due to privacy concerns. In the meantime, many researchers have been working on new technologies to enhance the privacy of individual mobility data to make them anonymous and unidentifiable (Hu et al. 2021c). Several studies have utilized data provided by mobile network operators to understand the spatio–temporal dynamics of the pandemic and effects of the recent COVID-19 pandemic on the transportation (McKenzie and Adams 2020; Liu et al. 2021d; Hu et al. 2021b; Hara and Yamaguchi 2021; Parker et al. 2021).

## 4 Challenges and limitations

There exist several challenges and limitations with respect to the usage of mobility data obtained via various sources. Among those, data privacy is the prominent one. The privacy concern differs based on the means of data collection. Within public data sets, such as those obtained through public transportation systems, privacy has lesser importance since the data usually comprise of aggregated human mobility such as scheduled timetables and actual aggregated travel records. Conversely, transportation companies and governments should ensure privacy of data that contain individual travel information. Within the survey data, on the other hand, consent of the participating individuals are taken overtly since the data collection process is based on the willingness and active participation of the individual.

Data obtained by mobile network operators and mobile phone applications are subject to more data privacy challenges. The main reason is that a variety of information regarding human activities are collected simultaneously and the consent of the user regarding the data collection process is usually obtained via an undertone agreement or the consent of the user is not taken at all. Hence, governments, data providers, and researchers have been making joint efforts to develop regulations that ensure ethics clearance in the process of data sharing and manipulation (Hu et al. 2021c). For instance, several researchers have proposed recoding and identity hiding procedures to make mobility data anonymous (Pelekis et al. 2012; Primault et al. 2015; Cerf et al. 2017).

Data quality is another issue for processing mobility data. The fidelity of the mobility data differs based on the data source. It is not uncommon to observe lots of missing values in data obtained from the transportation companies due to human errors of smart card users or malfunction of transaction devices (Hu et al. 2021c). Moreover, mobility data also suffer from lack of enough representativeness since mobile phone/application data are confined to mobile device users, in particular, to those who open their location on. Survey based mobility data also suffer from the same problem because survey respondents are more likely to be younger and belong to middle/upper income households. Hence, the fidelity and representativeness of the mobility data should be considered when performing analyses and drawing conclusions based on these data.

Accessibility of mobility data might be an important limitation for researchers. Most of the mobility data are confidential and authorities handling the relevant data are reluctant to share them due to privacy issues. Conversely, with the emerge of the COVID-19 pandemic, companies such as Google and Apple released anonymous aggregated mobility data for the researchers. Similarly, other companies and institutions have made human mobility datasets publicly available for researchers via different means such as (*i*) online dashboards of data providers, (*ii*) GitHub, (*iii*) Harvard Dataverse, and (*iv*) user applications (Hu et al. 2021c). These implementations are promising for future analyses that aim to mitigate the effects of pandemics/epidemics. Conversely, it has become evident during the COVID-19 pandemic that there exists a need for developing standards for collecting, storing, processing, and sharing the mobility data.

## 5 Conclusion

The relationship between the mobility and disease spread is a determinant factor in decisions related to public health. To mitigate the adverse affects of the pandemic data-driven analytics which rely on timely, rapid and accurate data played an important role in making effective

decisions. In particular multi-source and multi-faceted data is efficiently used in tackling several contemporary location and transportation problems faced during the COVID-19 pandemic.

Although we do not claim that we have exhaustively identified all emerging transportation and location related studies published during the pandemic, in this study we have identified major data streams that constitute the backbone of modeling and solution approaches. We have also provided an overview of basic problem types, decision problematics and implemented solution approaches.

Our results show that the power of OR tools and techniques are further strengthened with the inclusion of data obtained from multiple streams. These analytic approaches shed light on people's travel habits as well as governmental regulations regarding the mobility and other preventive actions.

Our review of the literature and relevant discussion has revealed some future research directions and outlook for transportation and location planning that will help mitigating the ill effects of future pandemics. With the abundant data available through passive data collection, further research are required to develop novel parallel and scalable computing algorithms, high-performance data storage, processing, and the ability to extract relevant and valuable information from the data (Hu et al. 2021c). The initial phase of the pandemic is particularly important for quick response and efficient transportation and location planning. In this phase, multi-faceted and up-to-date mobility data are required rapidly by researchers for the transportation and location related research. To that end, a good research direction would be to develop interactive geospatial web portals where researchers can access, query, and visualize relevant data. Additionally, due to multi-faceted characteristics of the mobility data, efficient data fusion techniques should be developed to enable researchers integrate multiple data sources and elicit relevant data rapidly. Standards should also be developed for collecting, storing, processing, and sharing multi-source mobility data. In terms of data privacy, efficient regulations that will ensure ethics clearance in the process of data sharing and manipulation are required.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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