Multimodal Transportation 1 (2022) 100030

Contents lists available at ScienceDirect

Multimodal Transportation

journal homepage: www.elsevier.com/locate/multra

Review

A survey of COVID-19 in public transportation: Transmission risk, mitigation and prevention

Xiaoli Liu*, Pranvera Kortoçi, Naser Hossein Motlagh, Petteri Nurmi, Sasu Tarkoma

Department of Computer Science, University of Helsinki, PL 68 (Pietari Kalmin katu 5), Helsinki 00014, Finland

ARTICLE INFO

Keywords:
COVID-19
Transmission mechanism
Public transportation
Transmission risk
Mitigation
Prevention

ABSTRACT

The COVID-19 pandemic is posing significant challenges to public transport operators by drastically reducing demand while also requiring them to implement measures that minimize risks to the health of the passengers. While the collective scientific understanding of the SARS-CoV-2 virus and COVID-19 pandemic are rapidly increasing, currently there is a lack of understanding of how the COVID-19 relates to public transport operations. This article presents a comprehensive survey of the current research on COVID-19 transmission mechanisms and how they relate to public transport. We critically assess literature through a lens of disaster management and survey the main transmission mechanisms, forecasting, risks, mitigation, and prevention mechanisms. Social distancing and control on passenger density are found to be the most effective mechanisms. Computing and digital technology can support risk control. Based on our survey, we draw guidelines for public transport operators and highlight open research challenges to establish a research roadmap for the path forward.

1. Introduction

Ever increasing urbanization has made public transportation a vital function of urban society. The COVID-19 pandemic is posing significant challenges for public transportation operations resulting in decline of demand and revenue (Tirachini and Cats, 2020) while being seen as a potentially contributing factor to the growth of major outbreaks (Dzisi and Dei, 2020). As scientific understanding of the pandemic is accumulating and evolving, it is important to understand to which extent the pandemic affects transportation and what measures are the most effective for mitigating the possible risks of transmission in public transportation. For example, while indoor environments generally are seen as posing higher transmission risks than outdoor environments (Nishiura et al., 2020), factors such as social distancing, ventilation, and air quality affect the overall transmission risk (Bhagat et al., 2020). While there are several studies on the transmission mechanisms of the SARS-CoV-2 virus which cause the COVID-19 disease (Harrison et al., 2020), there is a lack of understanding of how these findings relate to public transportation systems and what can be used to manage risks during public transportation. Similarly, while there have been efforts to study and survey different risk mitigation measures (de Bruin et al., 2020) including mask use (Feng et al., 2020), social distancing (Lewnard and Lo, 2020), and digital technologies (Gasser et al., 2020; Ting et al., 2020), their suitability for public transport has not been comprehensively assessed.

This article contributes by presenting a comprehensive survey of the current research on COVID-19 transmission mechanisms and how they relate to public transport. We critically assess literature through a lens of disaster management, synthesize and reflect on scientific literature drawn from transportation research, epidemiology, medical sciences, environmental sciences and computing. We cover the transmission mechanisms, risks, mitigation, and prevention mechanisms to establish the potential links and effects between

* Corresponding author.
E-mail address: xiaoli.liu@helsinki.fi (X. Liu).

https://doi.org/10.1016/j.multra.2022.100030
Received 20 December 2021; Received in revised form 10 May 2022; Accepted 11 May 2022

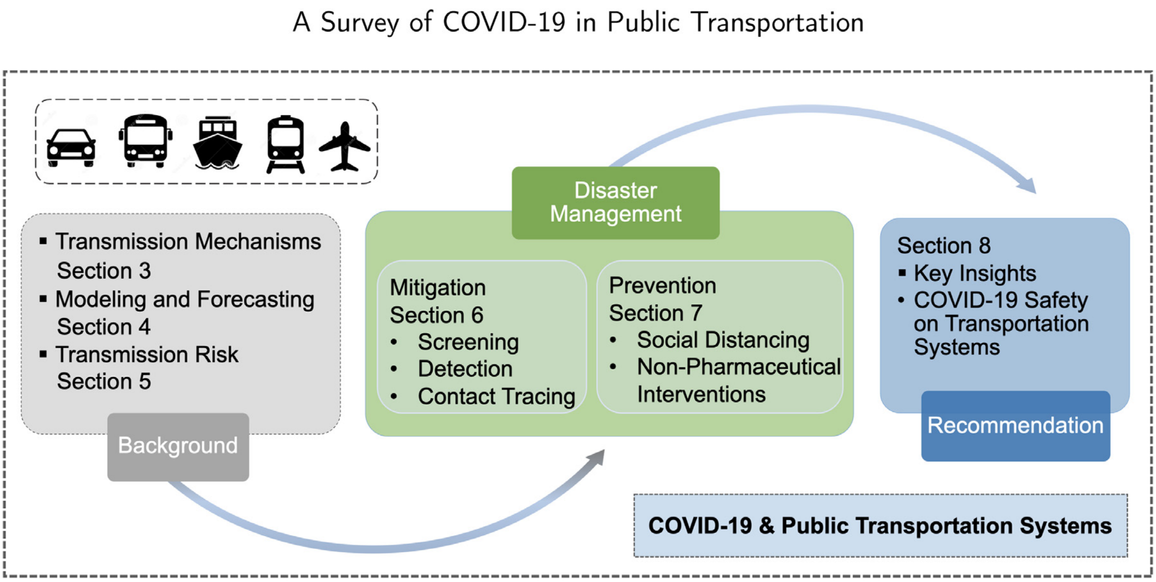

Fig. 1. Scope of the article presented as relationships among the different sections.

COVID-19 transmission and public transportation systems. We separate different transport modalities as much as possible and reflect on how the current scientific understanding relates to transmission risks and their management inside them. We also consider how different mediating factors – such as ventilation, lay-out and seat arrangement, occupancy rate, duration of the trip, passenger density, cleaning and hygiene – affect the transmission risk of the virus. Through our survey we derive novel insights that can be used to help manage risks inside different public transportation vehicles and identify open issues and challenges for the research community.

2. Scope and methodology

Public transportation providers are facing significant challenges due to the COVID-19 pandemic as plummeting passenger numbers have reduced revenue streams while in parallel the providers have needed to take additional measures to ensure the safety of passengers and vehicle operators. The severity and widespread global implications of the pandemic have also fueled significant research activity, with Google Scholar listing over 211 000 results for the keyword COVID-19 in 2020 alone, and over 60 500 for the first eight months of the year 2021. Despite this significant research activity, currently the scientific landscape relating to COVID-19 in public transportation has been understudied. Indeed, existing surveys on COVID-19 and transportation focus on the effect of the COVID-19 on public transport providers without considering the effects of the pandemic on the transit event itself. Our survey addresses this gap by providing a thorough review of the research field and mapping the road forward.

2.1. Survey scope

COVID-19 pandemic is a prominent example of a biological natural disaster and managing the response to the pandemic has many similarities to management of other disaster situations (Ricciardi et al., 2011). This view is also supported by the all-hazards theoretical framework for disaster management, which currently is the principal framework for disaster preparedness (Lettieri et al., 2009). This theory stipulates effective disaster management to be achievable through a consolidated strategy that covers different types of hazards. While there are some limitations to this theory, e.g., it offers limited adaptability for tailoring response to characteristics of a disaster situation (Bodas et al., 2020), it nevertheless provides a widely-used and unified theoretical framework that we use as a foundation for setting the scope of this survey. In a survey on disaster management literature, Lettieri et al. (2009) highlight common features of the all-hazards approach to be continuous monitoring for risks and a multi-phase response model. The canonical phases of the response model, which also are in line with the disaster management recommendations of the Federal Emergency Management Agency (FEMA), are mitigation, preparedness, response, and recovery. In this survey, we focus on the role of epidemiology, technologies and other potential mechanisms to support the mitigation, preparedness, and response phases of disaster management in public transportation systems. Specifically, we target solutions that pertain to the ongoing COVID-19 pandemic while also addressing their relevance for possible future pandemics.

The overall scope of the survey is illustrated in Fig. 1 and focuses on understanding the effects of COVID-19 on transportation systems. We first provide the necessary scientific understanding for assessing, evaluating, and understanding the effects and risks of COVID-19 by detailing the transmission mechanisms, modeling and forecasting of disease spread, and different risk factors in public transport systems (left part of the figure). We then contextualize these from the point-of-view of disaster management, focusing on mitigation, prevention and response phases (middle part of the figure) as these correspond to the main phases that public

Table 1
Existing surveys related to COVID-19.

Scope	Survey
Economics	Effects for economics and measures for mitigating them (Padhan and Prabheesh, 2021)
	Effects, social distancing, and government response (Brodeur et al., 2021)
Technology	Enabling and emerging technologies for social distancing (Nguyen et al., 2020a; 2020b)
	AI in image processing for COVID-19 (Shi et al., 2020)
Diagnosis	Different diagnosis methods and analytical efficiency (Giri et al., 2021)
	Role of Images and techniques for COVID-19 diagnosis (Dong et al., 2020)
	Image processing using AI for COVID-19 diagnosis (Shi et al., 2020)
Interventions	Potential measurements (surface disinfectants, hand sanitization, and personal protective equipment) for fighting against COVID-19 (Pradhan et al., 2020)
	Diagnosis, treatments, and prevention (Hafeez et al., 2020)
Transport	Rules for use of public transport, economic and social effects, and policy direction for intervention (Tirachini and Cats, 2020)
	Factors affecting COVID-19 transport measures and their effects (Shortall et al., 2022)
	Transport planning and adaptation (Gkiotsalitis and Cats, 2021)

transportation operators and individuals through their travel mode choice can have an effect. Finally, we synthesize the discussion by drawing recommendations for public transport on how to minimize risks and adverse effects of COVID-19 – and other potential respiratory illnesses (right part of the figure). Specifically, Sections 1 and 2 provide an introduction and present the scope of the article. Section 3 provides an overview of the virus transmission mechanism, offering the necessary background for understanding the SARS-CoV-2 virus and countermeasures against it. Section 4 details modeling solutions including epidemiological, forecasting, and mechanistic models which can be used to estimate transmission dynamics in the short and long term. These models are essential for assessing the risks and impacts of COVID-19 on a city-scale and help guide policy makers in making strategies to cope with the current epidemic situation. For example, if the number of infected people can be predicted beforehand, guidance could be given in advance before traveling. Section 5 details the risk factors that mediate transmission risk and discusses how they affect public transport. Section 6 focuses on the mitigation phase, covering traditional public health strategies such as screening and detection and how they can be augmented through technological means, such as using thermal screening and contact tracing. The section also provides recommendations for risk mitigation measures in public transports. Section 7 details prevention mechanisms including social distancing along with the monitoring technologies suitable for public transport systems, and the non-pharmaceutical interventions (NPIs). Section 8 discusses key insights and presents future outlook based on the survey, highlighting possible solutions while addressing potential research directions. Finally, Section 9 summarizes and concludes the survey.

2.2. Related surveys

Table 1 summarizes existing surveys related to different aspects of COVID-19 and disaster management in transportation systems. In terms of the former, there are surveys that provide a general review of the economic effects caused by COVID-19, government response, and measures for mitigating the adverse economic effects (Brodeur et al., 2021; Padhan and Prabheesh, 2021). There are also surveys on different technologies (such as wireless technology, machine learning, and computer vision) for supporting specific parts of disaster management. For example, there are surveys related to detection and mitigation that cover technological means for social distancing (Nguyen et al., 2020a; 2020b) and artificial intelligence (AI) in image data processing for COVID-19 diagnosis (Shi et al., 2020). These have focused on technologies without relating them with public transportation systems. Other surveys have provided a general overview on the intervention measurements for fighting against the COVID-19 (Hafeez et al., 2020; Pradhan et al., 2020). These surveys partially overlap in scope with our work from a general point of view but are not specifically linked to the public transport system. As highlighted, there currently is a lack of comprehensive research related to the COVID-19 pandemic and public transportation. Indeed, only isolated studies with a narrow focus have been carried. For example, Schwartz (2020) investigates the possible links between transit ridership and the number of infections, measures for risk mitigation, and service adjustments based on changes in demand. The international union of railways (UIC, 2020) has published a report that discusses the contamination on trains, but that does not provide a holistic understanding of the situation or potential measures that can be used to alleviate issues or a discussion of how to generalize to other means of transportation. Shortall et al. (2022) identify favorable contextual factors relevant to transport related measures from socio-economic, cultural, political, and individual perspectives, and discuss how those factors affect the measures. Gkiotsalitis and Cats (2021) cover planning requirements from the point-of-view of public transport operators and synthesize findings from research to provide an overview on how to best adapt operations against disruptions caused by COVID-19. Our survey focuses specifically on individual transit events instead of the operations of the transport provider. Finally, Tirachini and Cats (2020) focus on transport governance and provide an overview related to COVID-19 and transport, specifically rules (such as physical distancing, wearing face masks, hygiene, sanitization, and ventilation) for use of public transportation, economic and social effects caused by COVID-19, policies for pandemic response in public transportation. Unlike ours, the survey of Tirachini and Cats (2020) does not discuss COVID-19 related to individual transportation events or different means of transport, focusing instead on the governance of transport systems. Indeed, prior to our work, no article has systematically surveyed pandemic response of individual transit events. Our article addresses these gaps in these existing surveys, offering a complementary view, and providing

Table 2
Keywords used for collecting the papers.

Section	Keyword
3	transmission, mechanism, air pollution, airborne, pollutant
4	epidemiological, prediction, forecast, spreading
5	transportation, transport, bus, train, airplane, transmit, cluster, humidity, temperature, ventilation, filtration, mobility
6	crowd, contact tracing, screening, detection, diagnosis
7	social distancing, prevention, NPI

a comprehensive survey on the transmission mechanism, epidemiological and forecasting models, risk factors affecting transmission risks, mitigation and prevention measurements for COVID-19 on public transit.

2.3. Selection of articles

The articles are initially selected by searching recent research articles using a small number of keyword seeds on Google Scholar, PubMed, Scopus, medRxiv, Web of knowledge, IEEE Xplore, and ACM Digital Library. The queries combine a keyword from the set {`COVID-19`, `SARS-CoV-2`, `coronavirus`}, and a topic-specific keyword, summarized in Table 2. The initial article set is expanded by taking into consideration articles that cite or are being cited in the article set. We complement the set of articles by adding prominent research featured in media to cover a comprehensive set of important publications in this area. This process is continued until no new articles are found. We then discuss the papers among the authors and analyze the relevance and importance of the selected articles by reading the abstract and the main findings of the papers. Papers that are deemed less relevant for the scope of the survey are filtered out during this process. Some papers are relevant, but express quite similar opinions related to the topic. In such a situation, the papers are discussed among the authors and the most representatives are selected for inclusion. This is done to minimize overlap and ensure comprehensive coverage of all relevant topics. The final selected 168 research papers form the core of this survey paper, and we have performed minor updates during the survey writing process to cover papers published since the start of our process.

3. COVID-19 transmission

Preventing the spread of COVID-19 requires a comprehensive knowledge about the transmission mechanisms of the virus. We begin the survey by presenting an overview of the current scientific understanding of the COVID-19 transmission mechanisms. We cover the currently known transmission mechanisms and environmental contributors such as air pollutants to the transmission of the SARS-CoV-2 virus.

3.1. Transmission mechanisms

The pandemic has lasted for over two years and there is a better understanding of the SARS-CoV-2 virus transmission compared to the initial breakout. The current research understanding states that the main transmission mechanism is exposure to respiratory droplets containing the virus (Centers for Disease Control and Prevention, 2021). The exposure occurs mainly in three ways: through inhalation of air carrying the virus, virus deposition, or the hand touching the mucous membranes while containing virus particles (Centers for Disease Control and Prevention, 2021). Respiratory droplets are generated by exhalation and the resulting particles then remain suspended in the air. The time they remain suspended depends on their size, with two main groups being distinguished in the literature (Alsved et al., 2020). Larger droplets rapidly fall to the ground in close proximity to the source whereas smaller droplets can remain suspended in the air for several minutes – or even hours in some cases – and move away from the source with air currents. The smaller particles become diluted over time and distance as the volume of air they encounter grows. Traditionally, a threshold of 5μm has been used to differentiate between large and small particles. Specifically, droplets are particles that exceed 5μm in diameter, whereas droplet nuclei are aerosols that form when smaller respiratory droplets, of a diameter at most of 5μm, evaporate in the air. Inhalation of smaller particles, i.e., droplet nuclei, is also referred to as airborne transmission in the literature (Siegel et al., 2007; World Health Organization, 2014). Asymptomatic but infectious people can transmit the virus when they are close to another person (within 6 feet contact distance) and cough or sneeze – or even as they exhale during respiration or speaking. Public transport generally takes place inside crowded enclosed spaces and hence there can be an elevated risk of the SARS-CoV-2 virus transmission during the transit. As will be discussed later in the article, wearing masks and keeping a distance greater than 6 feet from other passengers have been suggested as ways to mitigate the risks.

The scientific understanding of the SARS-CoV-2 virus transmission is continually evolving, e.g., initially airborne transmission was considered unlikely (Lewis, 2020), but this has later been disputed. The most recent guidance by the WHO states that a virus can spread through both large and small respiratory droplets, and transmission can also occur during a prolonged stay in an enclosed space where the air contains viral particles (World Health Organization, 2021a). Indeed, laboratory studies have shown the virus to be able to remain active while suspended in the air for over an hour (Kampf et al., 2020; Van Doremalen et al., 2020). Therefore, a healthy passenger located further than 6 feet from an infected person can become infected due to the exposure to the virus suspended in the air over long distance. Furthermore, even when an infected passenger gets off the vehicle prior to a healthy passenger boarding the vehicle, it is possible for the healthy passenger to become infected by inhaling virus-containing respiratory droplets suspended in the air left by the infected passenger. However, airborne transmission over longer (i.e., non-contact) distance or time can only occur when the conditions are suitable (Morawska and Cao, 2020; World Health Organization, 2021b). Examples of conditions where such transmission has been reported include diverse enclosed spaces that have inadequate ventilation or air exchange (Li et al., 2007; 2020). Hence, good ventilation is essential for reducing the transmission risk of passengers.

Besides airborne transmission, the SARS-CoV-2 virus can also be transmitted through so-called *fomites*, which refer to objects or surfaces that become contaminated with the virus (Tellier et al., 2019). Fomites form when droplets carrying the virus are released by an infected individual (Asadi et al., 2019; Contini and Costabile, 2020) and fall onto a surface that becomes contaminated with the virus as a result. For example, seats and handholds can become contaminated in a vehicle. Passengers can then become infected by first touching a contaminated surface and then touching a mucous membrane. In laboratory studies the virus has been able to survive on surfaces even for days when the conditions are optimal (Van Doremalen et al., 2020). Viral particles can remain alive on the surfaces for hours increasing the threat for healthy passengers that use public transport systems. However, the overall role of surface-based fomites is contested as the average count of particles that are released is typically small compared to those used in laboratory studies. Indeed, recent scientific understanding suggests that fomites are a possible but not a prominent mechanism for disease transmission (Lewis, 2021). Regular cleaning the surface and personal hygiene are effective measurements for reducing the risk. However, due to the characteristics of the public transport system, such as enclosed space, hard to keep the social distance specially during the rush hour, and high mobility, the public transport is subject to significant challenges.

3.2. Transmission and air pollutants

Air pollutants and aerosols are widely considered as a mediating factor for the transport of the SARS-CoV-2 virus and they also are a factor that can affect the severity of the disease (Domingo et al., 2020; Hadei et al., 2020). The association between transmission risk and air pollution stems from studies of other respiratory diseases. For instance, there are studies that have shown a positive association between death sourced from SARS cases and air pollution (Cui et al., 2003) and similar studies have been carried out to investigate links between air pollutants and COVID-19 incidence and fatality rates (Contini and Costabile, 2020; Copat et al., 2020; Fattorini and Regoli, 2020; Wu et al., 2020). These studies have shown that both meteorological variables (i.e., temperature (T), relative humidity (RH), and pressure (P)) and air pollutants (particulate matter (PM) or diverse gaseous pollutants) can affect the risks and severity of infections. While there have been several studies exploring the impact of air pollutants and meteorological factors on SARS-CoV-2 transmission, there currently is no consensus on the pollutants that are the most significant factors to affect infection and mortality rates (Contini and Costabile, 2020). Table 3 presents a summary from the related studies. In the table, *positive correlation* refers to an increase of the number of COVID-19 infected persons, whereas *negative correlation* indicates a decrease of such a number. The term case refers to the number of infected people or the number of fatalities.

The studies summarized in Table 3 have not reached any unanimous conclusions, indicating that the relationships between meteorological factors, air pollutants and COVID-19 is intricate. The relationships of different variables are also potentially intertwined. However, some general trends have emerged from these studies. First, many studies correlate a high concentration level of particulate matter ($PM_{2.5}$ or PM_{10}), CO_2, NO_2, and relative humidity to an increase of the number of COVID-19 confirmed cases. In contrast, temperature (T), pressure (P), sulfur dioxide (SO_2) and ozone (O_3) have shown the opposite effect. The studies also suggest that industrial and urban areas may have higher incidence and mortality rates than rural and agricultural areas, even after adjusting for differences in population density. Similarly, areas with a PM concentration exceeding 50 $\mu g/m^3$ tend to have higher incidence rates. Both NO_2 and PM_{10} concentrations exceeding the mean concentration level have been associated with a higher likelihood of a positive test case and long term exposure to either pollutant is used as a measure to estimate the spreading of the COVID-19 (Saez et al., 2020). Note that these pollutants result mostly from traffic, and thus they also serve as a proxy for overall mobility. As such, the association with the COVID-19 may simply be a result of increased mobility and more studies are needed to fully uncover the role of air pollutants in spreading the COVID-19.

Reversely, public transport systems not only generate air pollutants but also continuously expose the passengers to them. The total exposure, however, also depends on many factors such as the seating location, route of the vehicle, and age of the transportation fleet. They all affect the extent to which a person is exposed to pollution (Motlagh et al., 2021b). The levels of air pollutants, temperature and humidity increase as a result of higher number of commuters in public transportation systems. As a result, higher pollution concentrations also serve as a proxy for crowding and human mobility, which in turn partially explains the higher risk of the COVID-19 transmission.

4. Modeling and forecasting

The transmission mechanisms of COVID-19, covered in Section 3, govern how COVID-19 spreads from an infected individual to another. For the purposes of transportation planning, however, it is also necessary to understand how transmissions between individuals propagate to the entire population. Indeed, lockdowns, international travel bans, and other restrictions on transit were among the earliest COVID-19 related countermeasures for stemming the tide of infections. This section covers the main approaches for modeling and forecasting infections within an entire population, and discusses how these findings relate to public transportation operations.

Table 3
Example studies based on air pollution and meteorology data analysis.

Case Study	Period	Analysis Method	Positive Correlation	Negative Correlation	Note
120 cities, China Zhu et al. (2020)	2020/01/23 & 2020/02/29	Generalized additive model and Spearman correlation	CO, NO_2, $PM_{2.5}$, PM_{10}, O_3, P, T, RH, and Wind Speed	SO_2	Reduction of air pollutants (except SO_2) can be useful approach in controlling COVID-19 spreading
154 cities, China Ran et al. (2020)	2019/12/10 & 2020/02/29	Spearman's rank correlation and Spline regression	—	O_3	O_3 concentration should be above a certain threshold
29 provinces, China Lin et al. (2020)	2020/01/21 & 2020/04/03	Regression analysis	CO	T and P	Efficient ventilation system reduces COVID-19
Kuala Lumpur, Malaysia Suhaimi et al. (2020)	2018/03/11 & 2020/04/21	Spearman's correlation test	$PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and RH	T	Data before COVID-19 time used to highlight long-term exposure to air pollution
Huanggang, Wuhan, & Xiaogan, China Jiang et al. (2020)	2020/01/25 & 2020/02/29	Multivariate Poisson regression models	$PM_{2.5}$ and T	RH and PM_{10}	Study period is short. Results may change by using longer period and more detailed data.
Milan and Florence Italy Lolli et al. (2020)	2019/03/08 & 2020/05/30	Kendall rank correlation tests and Non-linear Spearman	$PM_{2.5}$	T, Absolute Humidity, Dew Point, and Water Vapor	Virus transmission prefers dry and cool environments as well as polluted air
219 cities China Zhang et al. (2020)	2020/01/24 & 2020/02/29	Kendall and Spearman tests and multivariate regression analysis	AQI and RH	T	Higher wind speed may decrease infection risk.
Catalonia Spain Saez et al. (2020)	2020/02/25 & 2020/05/16	Generalized linear mixed models (GLMM)	NO_2 and to PM_{10}	—	Long-term exposure to NO_2 and PM_{10} are predictors of the spread of COVID-19

The names of the abbreviated variables are as follows. AQI: Air Quality Index, P: Pressure, T: Temperature, RH: Relative Humidity, CO: Carbon monoxide, NO_2: Nitrogen dioxide, O_3: Ozone, SO_2: Sulfur dioxide, $PM_{2.5}$ and PM_{10}: Particulate Matters with diameters of 2.5 μm and 10 μm, respectively.

4.1. Epidemiologic models

Epidemiologic models are important forecasting and planning tools that facilitate the work of policymakers, clinicians, and public health practitioners, and help keep people safe during epidemic outbreaks (Holmdahl and Buckee, 2020). Epidemiologic models are always abstractions that attempt to capture the key mechanisms governing the spread of infection and as such are limited by the intrinsic uncertainty of how to accurately parameterize them. This is particularly the case for new and emerging threats where the characteristics of the infection are not known or well understood in advance. In practice this means that epidemiologic models are always tailored to the situation in hand, with particular attention put on the amount of available data, the situations captured by the data, and the assumptions of the model. The factors that most affect a model are:

(i) **Spatial scale.** The geographical context – local, regional, national, or worldwide – of the data sets limits the model accuracy as well as its validity when applied to broader areas than that of the collected data.
(ii) **Population density.** The intercontact-rate of people is a function of the population density, and thus this parameter needs to be normalized to provide a clear interpretation of the data.
(iii) **Data.** While hospitalization and deaths are well-reported, data from people with light symptoms or those that are asymptomatic is less reliable. Such cases are difficult to capture accurately and thus the data is unlikely to provide a clear indication of the spread of the infection.
(iv) **Assumptions.** Oversimplified models can produce outputs that are misleading. For instance, it might sound intuitive to assume that people gain immunity after recovering from the infection but this may not be the case. Similarly, assuming asymptomatic people as healthy or non-infected/non-infectious could considerably underestimate the infection rates in the future.

Compartmental models are the most common type of epidemiological models. They estimate the spread of a disease by assigning people into different compartments over time, and estimating the spread of the disease within the population through interactions and progressions between the different compartments. A widely-used compartmental model for many infectious diseases, including the COVID-19, is the SEIR model, where S, E, I, and R represent *susceptible, exposed, infectious*, and *recovered* people, respectively (He et al., 2020). The classic version of this model accounts for four different ways that people can be affected by an epidemic. Specifically, the total number of people sums up to those S, E, I, and R by the disease. Future predictions of the spread of a disease rely on accurately defining key parameters governing the transmission probability, and thus also the reproduction potential of the disease.

A commonly used parameter is the *basic reproduction number* R_0 which evaluates the transmissibility rate of an agent causing the disease in a population that is susceptible to it (Delamater et al., 2019; Diekmann and Heesterbeek, 2000). R_0 is used extensively by public health care authorities to evaluate the developing transmission of an epidemic. The severity of the transmission of an agent can be deducted by R_0 as follows. If $R_0 > 1$, the infection is expected to spread further in the population, and thus a potential outbreak continues. A value of $R_0 = 1$ means that the number of infections remains stable, whereas $R_0 < 1$ signals that the spread of the disease is slowing down. In practice, the entire population rarely is susceptible as people may be immune or have already had a prior infection. The *effective reproduction number* R represents the effect of infectious cases further spreading the disease and thus causing secondary infections. The value of R is time and situation specific, and thus is not dependent on complete susceptibility of the population to the disease. As the effective reproduction number R does not rely on assumptions about the population characteristics, it is a better measure for characterizing the pathogen transmission probability during an outbreak.

4.2. Forecasting models

Epidemiological models are crucial building blocks upon which we predict the future course of an epidemic and forecast its progress in time. Forecasting models operate by learning data patterns and extrapolating these patterns to new data points that are in the near future using statistical or machine learning techniques. Forecasting models tend to suffer from a substantial decrease in accuracy as the forecasting time-window size increases, especially if the initial data set is small. In addition, data pertaining to epidemics, including the COVID-19, is bound to vary unpredictably. This intrinsic characteristic is due to the fact that the infection rate of an epidemic depends not only on the disease itself, but also on factors such as preventive measures that local, regional or global governments and policymakers implement.

Forecasting models can be classified into two main groups, *mathematical models* that are based on stochastic theory and *data science models* that are based on machine learning techniques (Shinde et al., 2020). Similarly, the approaches can be categorized based on the data sets that are used to run the forecasting models either as big data-based (e.g., data provided by the World Health Organization or national databases) or based on data collected via various social media communication platforms. The advantage of using big data, i.e., population statistic data, is that there is better coverage and thus the forecasting model is not prone to sparsity. In contrast, studies carried out in smaller data sets such as clinical data, are better suited to cases where a large-scale data collection is not feasible and the data from only a short period of time is needed. Such is the case of pharmaceutical industries and research labs when working with a new drug or vaccine (Shinde et al., 2020).

Bertozzi et al. (2020) show how epidemic growth, such as the spread of COVID-19, exhibit an exponential trajectory, especially in the early stages of the outbreak when public health interventions (such as social distancing, mask-wearing, and self isolation) are not yet in place. By applying the exponential model to new infections and reported death data, the authors were able to forecast the course of the epidemic for South Korea, Italy, Germany, France, Spain, UK, and US for the next 15 and 20 days. Other works (Dehning et al., 2020; Fanelli and Piazza, 2020; Nkwayep et al., 2020; Rahimi et al., 2021; Shinde et al., 2020) overview various short-term forecasting methods. For instance, the particle swarm optimization algorithm is often used to estimate the Susceptible, Infected, and Recovered (SIR) model parameters with a high accuracy (Putra and Mutamar, 2019). Mbuvha and Marwala (2020) and Qi et al. (2020) tuned the SIR model based on the number of reported infection cases in South Africa and China to forecast accurate infection rates. Salgotra et al. (2020) modeled the course of the SARS-CoV-2 virus spread in India by means of genetic programming algorithms.

The work in Bherwani et al. (2020) assesses the spreading of COVID-19 in India over a period of two weeks. The article uses the SEIR model with data from the first quarter of 2020 to establish a connection between socio-behavioral aspects – such as social distancing and mandates of other policymakers (i.e., nationwide total lockdown and suspension of tourist and e-visas for all tourists) – and the rate of population infected with the SARS-CoV-2 virus. The research reported not only an increase in the number of infections if mandates are eased but also found correlation of such numbers with different environmental parameters such as temperature and humidity, mirroring the studies described in the previous section.

Similarly, other works by Ribeiro et al. (2020), Roosa et al. (2020a), and Roosa et al. (2020b) focus on forecasting COVID-19 cases in the near future. For instance, research by Ribeiro et al. (2020) forecasts the progress of the COVID-19 over a period of one, three, and six days in different Brazilian states. The forecast evaluation is based on a data set of cumulative confirmed cases until 19 April 2020, and leverages different machine learning models. The models achieved, on average, an error of 0.87% 3.51%, 1.02% 5.63%, and 0.95% 6.90% for one, three, and six days, respectively, suggesting that they are accurate for short periods of time and should otherwise be interpreted with caution. Similarly, Roosa et al. (2020b) generated 5- and 10-day forecasts based on cumulative cases reported in two provinces in China up until mid February 2020. Best results were obtained using a so-called sub-wave model (Chowell et al., 2019) that considers each spike of infections as a sub-wave and models the overall disease progression as a trajectory that aligns with these spikes. This suggests that forecasting models may work best when they support complex and varying dynamics in the different phases of the outbreak. It is important to stress, however, that the results of any forecasting models are always susceptible to the way the cases are modeled and how the parameters are defined. Nevertheless, forecasting models are important tools for estimating short-term developments and, as such, are highly relevant for public transport operations, e.g., by predicting the possibility of new countermeasures and making demand predictions.

4.3. Mechanistic models

Mechanistic models, unlike forecasting ones, provide long term projections of infection rates, hospitalizations, and deaths (Holmdahl and Buckee, 2020). These models consider different parameters that are strictly related to the infectious disease itself, as well as the actions taken by governments and corresponding authorities. For instance, disease-related parameters include (i) transmission methods (e.g., airborne particulates, breathing, physical contact with infected person and objects touched by them), (ii) ease of transmission (e.g., minimum time of exposure to infected person or objects), and (iii) possible immunity triggered upon recovering from the infectious disease.

The model forecasts are a function of the used methods and of the (possible) interventions that policymakers can implement. Both types of parameters can be modified at any moment in time as the understanding of COVID-19 and its transmission increases. Similarly, control measures are constantly tailored to the situation at hand. This up-to-date non-linear feedback on the current situation leads to a higher accuracy of the model projections. By injecting these information into the models, the long-term projections are best suited to assist policymakers with the next steps toward a safer environment.

The dynamics of an epidemic, though, are too complex to be represented by such a relationship. Therefore, many other non-linear features such as the seasonality and the stochastic nature of infections are introduced into the model. As an example, He et al. (2020) introduce additional variables such as the *susceptible class, infections with and without intervention, quarantined*, and *hospitalized*, alongside with system parameters such as temporary immunity rate, rate of transitioning from exposed to infected class, rate of recovery of symptomatic people, and the rate of transitioning from quarantined to the recovered class to produce a new flowchart of a tailored SEIR model. Another example is presented in Reiner et al. (2020) where a SEIR model is fitted on real case and mortality data to model expected infection trajectories and the effects of different non-pharmaceutical interventions on case trajectories. The study also covers the effect of social distancing mandates (SDMs) such as closure of schools and other nonessential businesses, stay-at-home mandates, and limitations regarding gatherings and recreational activities at reducing the infection rate. Overall, the models suggest that lowest infection rates and fatalities are obtained with a high rate of mask usage.

The work in Rădulescu et al. (2020) investigates the effect of different disease prevention management strategies, pointing out that in the first stages of the epidemic a relatively low mortality rate (around 3.3%) was observed. While this is comparable to that of less threatening and common epidemics (e.g., the seasonal flu), the spread factor R_0 however was bigger (≈ 3). This raised concern and triggered international coordination regarding travel bans or functional shutdown of certain non-indispensable economic branches.

Entertainment and recreational activities were among the last to close during the exponential growth of the pandemic. Not only they are a viable source of hotspots, but their closure affects only the corresponding group category, similar to the effects of closing schools or kindergartens. In addition, hygiene measures show a wide variability of overall acceptance and abiding, while more strict measures such as total lockdown and long-term isolation might yield non-negligible psychological effects in the population. Regardless of several measures implemented locally or world-wide, COVID-19 has already shown several subsequent waves and hotspots. This suggests that the timing, scheduling, and efficiency of these measures requires further optimization (Rădulescu et al., 2020).

Better understanding of these factors can improve existing SEIR models to generate informed predictions of long-term sustainable mitigation strategies with the least impact on the economy and mental well-being of the population. Accurately modeling the spread of SARS-CoV-2 is a fundamental step toward identifying risk factors – whether environmental, logistic, policymaker-related, or individuals' behavioral patterns – that might increase infection rates. The effects of such risk factors can be exacerbated in physically-constrained environments, such as public transport, which are characterized by large flows of people that move in given directions (e.g., people must follow strict path ways to get out of an underground metro station) and thus exhibit certain mobility patterns. This knowledge can thus be used to assess the risk of infection and design appropriate mitigation strategies to the situation at hand.

Table 4 summarizes forecasting and mechanistic models used in the literature to predict the spread of the SARS-CoV-2 virus in the short (e.g. days or few weeks) and long term (e.g., months or 1-2 years), respectively.

5. Transmission risk

Infected and often asymptomatic people expose others in their proximity to the virus and potentially carry the virus to other cities during the incubation period through traveling. The COVID-19 pandemic has spread globally and infections are drastically higher in cities compared to rural areas, which has led to worries of public transit being a major cause for outbreaks (Schwartz, 2020) and to fears of public transportation usage. To ensure safe operations of public transportation and safe travel of citizens, it is vital to have a detailed understanding of the possible factors affecting transmission risks and how they relate to public transportation systems. Below we discuss these in detail.

5.1. Risk factors

While public transportation vehicles represent enclosed indoor spaces, the transmission risks inside them are mediated by various environmental, social, and behavioral factors. Below we summarize the current scientific understanding about the factors that mediate COVID-19 transmission risks.

Seating location and duration of transport. Seating location affects the physical distance to other people and therefore it can affect the risk of disease transmission. One way to characterize the transmission risk associated with a specific seat is to use the so-called *attack rate* of a seat which characterizes the likelihood of being at risk of disease transmission (Hu et al., 2020). Immediately occupying a seat that is previously occupied by an infected individual has an attack rate of 0.075%, i.e., a relatively low risk of

Table 4
List of models to forecast the spread of the COVID-19 disease in the short and long term.

Reference & Authors	Model	Forecasting method	Forecasts submitted
Bertozzi et al. (2020)	Forecasting	Parsimonious SEIR model	Viral infection rate
Putra and Mutamar (2019)	Forecasting	SIR model with particle swarm algorithm	Infected and recovered cases
Mbuvha and Marwala (2020)	Forecasting	SIR model based on reported infection cases	Infection rates in South Africa
Qi et al. (2020)	Forecasting	SIR model based on reported infection cases	Infection rates in China
Salgotra et al. (2020)	Forecasting	Genetic programming algorithms	Viral infection rates in India
Bherwani et al. (2020)	Forecasting	SEIR model based on 3-month data	Infection rates as a function of environmental parameters (temperature and humidity) and various policymakers' mandates in India
Ribeiro et al. (2020)	Forecasting	Machine learning models	Progress of COVID-19 over a period of 1, 3, and 6 days in Brazilian states
Roosa et al. (2020b)	Forecasting	Sub-wave model based on cumulative reported cases	Progress of COVID-19 over a period of 5 and 10 days in two Chinese provinces
Holmdahl and Buckee (2020)	Mechanistic	SEIR model with non-linear feedback of biological features of virus transmission	Long-term epidemiologic outcome of COVID-19 under different policy responses
He et al. (2020)	Mechanistic	SEIR model with additional variables such as infections with and without intervention, quarantined, and hospitalized, as well as system parameters such as temporary immunity rate, rate of transitioning from exposed to infected class, etc	Spread of COVID-19
Reiner et al. (2020)	Mechanistic	SEIR model fitted on real case and mortality data	Expected infection trajectories and effects of non-pharmaceutical interventions on case trajectories
Rădulescu et al. (2020)	Mechanistic	SEIR model	Effects of disease prevention management strategies such as non-pharmaceutical interventions and strict measures (e.g., total lockdown and long-term isolation) in the spread of COVID-19 infection

transmission, whereas passengers that are within three rows and five columns of an infected passenger can reach an attack rate of up to 10.3% (Hu et al., 2020). The attack rate increases with physical proximity and persons occupying the seats in the immediate vicinity of an infected individual have the highest risk of disease transmission (Zhen et al., 2020). However, also the duration of travel and the ventilation of the carriage influence the risks. As an example, a case study related to potential disease transmission during a bus trip with an infected person was carried out and in total 243 individuals were investigated (Luo et al., 2020). Of these people, 12 later are tested positive. None of the infected cases wore a face mask, which was the most important factor to elevate transmission risk. As another example, a 10 h airplane journey has been investigated to assess risks of in-flight transmission (Khanh et al., 2020). Out of 217 passengers 16 got infected. The only symptomatic person traveled in business class and in total 12 of the 16 cases are reported with other business class passengers. We note that the study is conducted prior to mask recommendations becoming widespread and that the movements of the passengers were not tracked prior, after, or during the flight. As a result, infections could have already existed prior to travel or they might have been caused by other behaviors rather than the flight. As these two case studies highlight, the closer a person sits to an infected individual the higher the risk of infection. The results also show that even more spacious seating arrangements, such as those in airplane business class, are not guaranteed to ensure the safety of the passengers, and that long duration of travel and lack of mask use can significantly increase the risk of disease transmission. Recent research also investigates how to assign the seat in order to reduce the transmission risk while having an acceptable number of passengers which is helpful both from passengers and transportation system aspects (Pavlik et al., 2021).

Ventilation and filtration. Air ventilation and filtration can be used to mitigate risk of COVID-19 transmission and the current recommendations suggest both to increase the rate of outdoor air ventilation and to improve air filtration (Katzer, 2020). The concentration of virus in the air is generally lower when air exchange rate is high (Riffi, 2020) and it has been argued that increasing ventilation rates to reach a sufficiently high rate can significantly reduce the transmission possibility of SARS-CoV-2 virus– as well as the transmission of other flu-type viruses. The recommended rate of air exchange is twelve times an hour. In public transportation, and especially urban transportation such as subway, buses, and trains, the air circulation rates are typically closer to 18-times an hour, i.e., 50% more frequent compared to the recommended criteria. Alternatively, efficient air filtration systems can reach similar results as effective air circulation systems (Zhu et al., 2012) and even opening the windows of the carriage can help to reduce risks. Airplanes, in contrast, use so-called displacement ventilation where air enters from the floor and exists through the ceiling. Hence, displacement ventilation does not cause air to pass among passengers and this can further help to reduce the virus transmission risk. The effectiveness of ventilation and filtration is also dependent on the age of the transport fleet with modern vehicles typically having better ventilation and filtration systems than older ones. Taken together, the current scientific understanding suggests that effective ventilation and filtration are important for reducing transmission risks, particularly for aerosol transmission. However, contact and droplet transmission occurring in close proximity remains a threat and other measures, such as social distancing and face masks, are equally important.

Temperature and humidity. Both the temperature and the relative humidity can affect the rate at which SARS-CoV-2 virus decays. The Department of Homeland Security (DHS) has developed predictive models that can be used to estimate the decay time in different temperatures and (relative) humidity conditions. Generally, increasing temperature and relative humidity accelerates the speed at which the virus becomes inactive (Biryukov et al., 2020) and restricts the travel distance of droplets (Noti et al., 2013). Temperature also affects the survival rates of SARS-CoV-2 virus. Recent research work shows that the virus inactivation time can drop from approximately two days to mere hours when the temperature increases from 20° C to 40° C (Riddell et al., 2020). The correlation between temperature, humidity and the effective reproduction number of the SARS-CoV-2 virus is analyzed by using data from China and US. The analysis is adjusted to control for geographical, socio-economical, demographic and other potential mediating factors to ensure unbiased estimates. The results show a negative correlation for both temperature and humidity with the virus, and the effect is smaller post interventions (lockdown). Nevertheless, temperature and humidity affect transmissibility of the SARS-CoV-2 virus but they alone are not sufficient for controlling the virus. Indeed, in all of the authors' analysis, the effective reproduction number exceeds 2.5 when no interventions or countermeasures take place. These findings highlight that mitigation strategies and countermeasures are essential throughout the year.

Physical distancing and wearing mask. Physical distancing is one of the most effective actions to mitigate the transmission risk. Badr et al. (2020) investigate the role of social distancing on the new infection rate, where they try to formulate the distancing matrix based on the mobility trend generated from mobile phone data. The study shows that not only people already implement social distancing – despite the lack of a centralized (nationwide) recommendation and guideline system – by reducing their mobility by 35–63%, but also that social distancing slows down the transmission rate. The effects can only be seen after a period of 2–3 weeks, which coincides with the incubation period of the virus. Wearing masks significantly reduces airborne transmission, particularly in enclosed spaces (Prather et al., 2020). Wearing a face mask and keeping a distance of more than two meters (six feet) apart results in the lowest infection risk. Farther distances increase protection, but generally distances of one meter or higher already provide good protection (Chu et al., 2020), especially when combined with face mask use. Respirator masks, such as N95, provide better protection than disposable surgical masks and eye protection can further decrease infection rate. Nevertheless, none of these solutions is completely effective and in practice combining face mask use with physical distancing, effective ventilation and other measures, is the most effective strategy. Mask effectiveness is also dependent on the mask being properly worn and on the mask having a good fit, further motivating the need to combine multiple intervention strategies.

5.2. COVID-19 transmission in public transportation

Estimating the overall transmission risk or infection rate during travel is highly complex. Indeed, as discussed above, many factors affect the risk of disease transmission and there are complex interdependencies between the factors that make it difficult to estimate the overall risk. UIC had published a state of art for addressing the contamination rate on trains in 2020 (UIC, 2020). We will briefly survey the main approaches for modeling and estimating transmission risks in public transportation.

Model-based approaches attempt to construct statistical models that can be used to provide an estimate of the overall risk given different parameters of the travel. As an example, the Rail Safety and Standards Board (RSSB) together with collaborators has developed an approach for estimating travel risk in a train by considering three elements: number of person contacts during the whole journey (including in the station buildings, during boarding, in the train, disembarking, and exiting the station), risk of infection per person contact, and the impact of mitigating factors (including wearing masks, ventilation and filtration) (Hunt, 2021). The model is based on input values derived from data obtained from the UK and the infection risk is reported as below 0.01% per average journey with exact values depending on the type of carriage and if masks are worn. On average, the model estimates the risk of infection to be one infection per 11 068 journeys when no face masks are worn and one infection per 19 765 journeys when face masks are worn, respectively. The European Union Agency for Railways conducted a study to investigate the travel safety of passengers using train and other transport modes in long distance travel by building a mathematical model that estimates the increase in COVID-19 infection risk for passengers by considering the probability of a passenger being contagious, the probability of the virus being transmitted from the contagious passenger to a healthy passenger, and the probability of death or hospitalization due to the disease (European Union Agency for Railways, 2021). The model suggests that rail travel is safer than a car for long distance travels. The safety in this place is mainly related to the low risk of death or hospitalization from the SARS-CoV-2 virus infection. Generally, it is difficult to build a model to estimate the infection rate in the transportation system. Indeed, it is hard to track the passengers' contacts, their mobility during the travel event, and the later infection status. Therefore, there have been efforts to investigate the transmission risk using simulated virus particles. For example, Silcott et al. (2020) focus on modeling the aerosol transmission risk in flight and find the risk of disease transmission to be very low. Note that this only holds for aerosol transmission and contact or droplet transmission in close physical contact has much higher risk of transmission. The international air travel industry also recently has issued guidance related to flight travel, suggesting the transmission risks to be very low (IATA, 2020). As discussed, these findings need to be taken in their corresponding contexts as countermeasures such as face masks and social distancing, and behaviors before, during, and after the transit also play a major role in disease transmission.

Transit ridership-based approaches investigate the relationship between transit and COVID-19. Early research focuses on assessing the potential links between transportation volume and the spread of COVID-19 infections. For example, Zheng et al. (2020) investigate how public transportation affects the spatial transmission of COVID-19. They try to identify the relationship between the transportation frequency from Wuhan, the daily number of infections, and the cumulative total of infections in cities which have transportation connection with Wuhan. The analysis shows that there is a positive association, which indicates that the public transportation can import COVID-19 to other cities within the same country. However, the study focused on the initial phase of the outbreak in China, before any lockdowns or other measures were in place, and specifically on public transportation bringing imported cases to other cities rather than on the risks during the transportation process itself. Similarly, Kraemer et al. (2020) show that correlation between the number of infections and travel between cities is strong during the initial breakout stage. Cartenì et al. (2021) also showed that a positive correlation existed between the number of confirmed cases and the volume of the public transport trips carried 17 to 26 days ago for the period of September to December 2020 in Italy. Schwartz (2020) surveyed 1 300 patients admitted into New York City hospitals in early May 2020. Only 4% of the patients had recently used public transport. Indeed, the study reports that for most cities in the US, the correlation between infection rate and transit ridership was weak or even negative. Thus, separating the effect of the transportation effect from mobility, cultural and other factors is challenging.

Conversely, the human mobility patterns have suffered great changes due to the pandemic caused by COVID-19. For example, Huang et al. (2020) use data collected from Baidu Maps to investigate the impact of COVID-19 on human mobility and behavior. The proportion of people visiting residential areas greatly increased while the proportion of people using transportation systems decreased dramatically. Similar findings have been reported in numerous other studies. For example, compared with other transport modes transit, the transit of public transport decreased drastically during the spring of 2020 in the three most populated regions of Sweden (Jenelius and Cebecauer, 2020). Similar findings were obtained from a study in Istanbul which showed public transport ridership to decrease during the COVID-19 compared to the period pre-COVID-19 (Aydin et al., 2022). According to the study, people prefer to use travel modes with few contacts, such as private cars, biking, and walking to avoid infection. However, the distribution of different public transport modes, such as metro and different buses, was similar between the pre-pandemic and the pandemic period (year 2019 compared to January-April of 2020). In another study, the public transport ridership changes in ten US cities was analyzed for the first five months of 2020, and the public transport ridership decreased significantly since the beginning of the pandemic with the heaviest decline immediately after the start of the pandemic (Ahangari et al., 2020). Another study related to public transit changes in the US using data collected from mobile phone applications also shows the decline of transit (Liu et al., 2020a). There have also been many studies related to the impact of COVID-19 on travel mode choice (Beck and Hensher, 2020; Luan et al., 2021; Shakibaei et al., 2021) and how this impacts the transport operators (Gkiotsalitis and Cats, 2021). Detailed comparison of the studies is difficult due to differences in the socioeconomic context and characteristics of the public infrastructure at different locations. For example, the stage of the COVID-19 pandemic and the overall socioeconomic situation of the country (or city) affect travel choice. For example, in some locations people had limited options to use public transport during the pandemic and instead shifted to motor vehicles (Shakibaei et al., 2021). People also have suggested that they plan to return to pre-pandemic use of public transportation as the restrictions are eased and the pandemic situation stabilized (Przybylowski et al., 2021). Finally, human mobility patterns changes on transport modes due to COVID-19 in ten countries are investigated and it indicates that airplanes and buses might suffer higher infection risk compared with other transport modes (Barbieri et al., 2021).

Cluster-based approaches are a top-down method that observes actual infections and try to identify the source of transmission. COVID-19 cases often appear in clusters and understanding the factors causing these clusters can thus help combat the virus. A systematic review of the main cluster types in the literature identified 108 different types of clusters, only one of which corresponded to transportation (Liu et al., 2020b). Another systematic review (Leclerc et al., 2020) of available literature reports 22 clusters for 211 transmission events, with only one event connected with transportation. Furuse et al. (2020) analyzed 3184 cases of coronavirus disease in Japan for the period from January 15 to April 4, 2020 and identified 61 clusters. Health care facilities are the primary source of clusters and one transportation-related cluster was identified – linked to an airplane journey. A study conducted in Paris from early May to June 2020 found that none of the city's 150 coronavirus clusters came from transportation systems. The only four clusters related to transport were identified during 15th to 28th July in Paris, which accounted for about 1% of all 386 coronavirus clusters (Joselow and News, 2020). Meanwhile, Ireland publishes weekly report where the infection categories are well documented, for example, one infection out of 199 confirmed cases is related to travel for week 41 in 2021, no infection is related to travel for week 40 in 2021, and one infection out of 203 confirmed cases is related to travel for week 39 in 2021 (Health Protection Surveillance Centre, 2021). The clusters' information in North Carolina is updated every other week and there is no transport or travel related cluster in the main tracked cluster categories in the latest report updated on October 25, 2021 (North Carolina Department of Health and Human Services, 2021). The possible reasons might be the infection risk in transportation is not high due to the high vaccination rate and protective measurements, or it is hard to track the infections from the transport. In contrast to these results, analysis of 318 outbreaks in China excluding Hubei province involving 1245 confirmed cases in 120 prefectural cities during 4th January to 11th February found that 34% of the outbreaks were associated to transport, which was the second most important category following households (Qian et al., 2021). However, it is not possible to determine the mode of transport and corresponding duration for the transport category. The main challenge with cluster-based approaches is that their accuracy usually depends on voluntary cooperation and patients may not recall or want to disclose their entire contact history. These studies nevertheless indicate that transportation generally is not the primary source for infections. However, transportation is often needed to go to venues that end up being the main source of infection and thus there are risks of disease transmission during the transit periods, even if they would not be the primary reason for outbreak clusters.

Staff-based approaches compare the infection rates of transportation staff to the general public in an attempt to see whether transport has elevated risks of disease transmission. A study by the German railway company (Deutsche Bahn (DB) Fernverkehr AG) investigated the infection rate of the operational staff to identify the main transmission mechanisms of the virus, to better understand the current health situation of the employees, and to guarantee safe traveling for customers and safe operation for employees (Gravert et al., 2020). The infection rate of the board service staff and train attendants was found to be statistically significantly lower compared to the general population (0.26% vs. 0.36%). Finland railway company VR also carried out a study to compare the infection rate of VR employees compared to general populations in Finland by using data recorded on 1st February 2021. The infection ratio of VR employees is lower compared to the infection ratio of general population in Finland (0.62% vs. 0.82%), specifically, the infection ratio of VR long distance employees is lower compared to the general population (0.34% vs. 0.82%) and the infection ratio of VR short distance employees is a little bit higher compared to the general population (0.92% vs. 0.82%). Protective masks, social distancing and other measures that are in place can help to reduce risks for transport staff, even if individual journeys have the possibility of spreading the disease.

6. Mitigation

Mitigation seeks to reduce the impact and negative consequences of hazards. In disaster management literature, mitigation is traditionally seen as a phase that takes place prior to the disaster. However, during a continuous natural hazard, such as the COVID-19 pandemic, mitigation is actively pursued throughout the entire lifetime of the disaster. The main methods for mitigation are screening and detection. The former focuses on early identification of people that are potentially at risk, whereas the latter focuses on identifying people that have already been affected. Below we briefly summarize the main mechanisms for screening and detection and discuss how they relate to public transport.

Scent dogs can be used for early screening of infections, particularly for asymptotic people. Scent dogs have been shown to be capable of detecting early signs of infection with as little as one week of training, reaching an average diagnostic sensitivity of 82.63% in one study (Jendrny et al., 2020). The main use for scent dogs is at major transit hubs, such as airports or large railways stations, where they can offer a cost-effective way to perform pre-screening of large passenger volumes. As an example, the Helsinki airport adopted scent dogs in 2020 through a test where a skin swipe is presented to a scent dog (Nations, 2020). Individuals testing positive were then directed to a laboratory PCR test to verify the diagnosis.

Thermal screening refers to the use of thermal cameras for identifying people whose body temperature is elevated. The main benefit of thermal screening is that it does not require contact, i.e., it is a non-invasive method for screening individuals. Similarly to scent dogs, the main use for thermal screening is at airports and other large commuter hubs – or points-of-entry – where the volume of passenger traffic is significant. Indeed, the main potential for thermal screening is to offer a passive solution for screening at locations where traditional care methods are not practical or otherwise feasible (Maguire et al., 2021). Besides transit hubs, there have also been solutions that integrate thermal screening in other public transport. For example, South Korea deployed smart shelters that are equipped with air-conditioning, ultraviolet light air sterilizers, and thermal cameras that allow only people whose body temperature is below 37.5° C to enter the bus. The main limitation of thermal screening is that thermal cameras have limited sensitivity (Emenike et al., 2021; Malmivirta et al., 2019). For example, off-the-shelf FLIR technology has an average error of ± 2° C whereas more accurate technologies cost significantly more and require special cooling mechanisms. Another challenge with thermal screening is that the measurements are dependent on the body part that is monitored (Dzien et al., 2021), with the best and most consistent results coming from the side of the face and especially from the earlobe at a distance of at most 50 cm (Chan et al., 2004). Finally, thermal screening can only identify individuals that are already symptomatic. Thus, currently there is very little support for thermal screening to be an effective method for limiting the spread of COVID-19 (Cardwell et al., 2021).

Contact tracing is a key mechanism for slowing down the spread of COVID-19 – and other communicable diseases. Contact tracing identifies people that have been in possible contact with an infected person, directs them to testing, and encourages them to avoid contact with others until their disease status is known (Eames and Keeling, 2003). Traditionally contact tracing has been implemented using manual interviews and personal contact to individuals at risk of disease exposure (Klinkenberg et al., 2006), but such efforts are only feasible when the number of infections and the potential exposures remain small (Farrahi et al., 2014; House and Keeling, 2010). Digital contact tracing augments this process using smartphone-based monitoring tools that can inform individuals if they are at risk of infection due to having been in contact with an infected individual (Ferretti et al., 2020). While digital tools for contact tracing have been available previously (Sacks et al., 2015), only the current COVID-19 pandemic has made their use widespread due to the availability of programmable tools for contact detection (Anglemyer et al., 2020). These apps use short-range wireless communication technology, such as Bluetooth, WiFi or ultra wideband to detect people within proximity of each other and later contact the people that are known to have a close contact with an infected individual (Nguyen et al., 2020a). Many governments have released contact tracing apps for COVID-19. Ensuring the privacy of individuals is a key design consideration for contact tracing (Cho et al., 2020; Morley et al., 2020). For more details on contact tracing we refer to a comprehensive survey by Ahmed et al. (2020) which covers system architecture, security, privacy, data management, and proximity estimation techniques. In terms of effectiveness of contact tracing, Kretzschmar et al. (2020) found the coverage of tracing and the delay between testing and tracing being the most important factors for achieving effective contact tracing.

Testing is the only guaranteed way of detecting individuals that are infected. The available testing methods are continually evolving with the main differences relating to the accuracy, intrusiveness, and costs of conducting and analyzing the results. Detailed coverage of the test mechanisms is outside the scope of this survey and we refer to the papers of Guglielmi (2021), Yuan et al. (2020) and Carter et al. (2020) for more details of the different tests. Public transport providers can play an important role in facilitating large-scale testing by supporting passengers in finding their nearest testing center and by providing guidance on how to reach there without putting others at risk.

7. Prevention

Prevention is defined as regulatory, physical and other measures that strive to ensure that hazards are prevented or their effects are mitigated. Prevention is thus complementary to mitigation, which typically operates prior to the occurrence of a hazard and focuses on mitigating the possibility of the hazard taking place in the first place. In case of COVID-19 pandemic, full prevention is only possible by isolating people and completely avoiding contacts and hence the prevention phase focuses on mitigating the impacts of potential risks. The main prevention measures that are related to public transport are social distancing and different non-pharmaceutical intervention measures. Below we discuss these mechanisms and their role in public transport.

7.1. Social distancing

Social distancing is an essential method for limiting the spread of diseases by minimizing the physical contact between individuals. As discussed in Section 5.2, the infection risk during a transportation is linked to the number of contacts, the number of people infected by virus and susceptible co-passengers, passenger density, and the total travel time. In practice, this means that, in the context of public transportation, social distancing refers to controlling the passenger density inside vehicles, e.g., by limiting the number of passengers at a given time, by blocking certain seats, or by adopting real-time monitoring technology that identifies possible risks and informs the passengers of them.

Crowd detection is the main technological solution for supporting social distancing. A common approach for crowd detection is to rely on wireless communications technology (Nguyen et al., 2020a; 2020b) such as Wi-Fi, Bluetooth, Ultra-wideband, and Zigbee or RFID. The main idea is to identify and track the position and location of passengers using signals from their devices and detect crowds by analyzing the locations of these devices.

The main alternative is to rely on camera-based methods which have a long tradition in crowd monitoring and crowd density estimation (Junior et al., 2010). Camera-based methods traditionally use standard cameras, and apply computer vision techniques (Li et al., 2008) for crowd detection and people counting. While images provide rich information about interactions between individuals and occupancy, they can be extremely intrusive as they capture sensitive and private data of people, e.g., facial features. Obfuscation techniques, such as blurring, can be applied over images to protect individuals (Chan et al., 2008), but these require intensive processing over the images, which is difficult to achieve in real-time. Privacy concerns can be alleviated by adopting thermal cameras for crowd detection (Abuarafah et al., 2012; Flores et al., 2020; Rinta-Homi et al., 2021). The use of direct thermal radiation estimates is similarly intrusive as the use of regular cameras, but it is also possible to rely on indirect measurements of individuals that result from interactions with the environment. Indeed, when individuals touch objects or even walk, thermal footprints caused due to their human-emitted thermal radiation are visible. By analyzing this residual thermal information (Emenike et al., 2021), it is possible to understand not just occupancy of the room, but also the density of interactions that the room has experienced from people visiting it. Another approach is to use air quality sensors to measure $PM_{2.5}$, CO_2, (relative) humidity and temperature for extrapolating the occupancy in the spaces (Motlagh et al., 2019). For example, an increase in CO_2 level or temperature in a room can be caused by a higher number of people inside a room (Motlagh et al., 2021a). Naturally, these estimations require also to know other factors like room dimension and space distribution. While this method can provide meaningful data about the amount of people in an area, it fails on providing insights about individuals' proximity. Variations in temperature and CO_2 levels can also be used to distinguish between indoor and outdoor areas, which can be used to separate cases where devices are in close proximity but separated by a barrier. Finally, sound measurement can be used for identifying the crowd by using different spectrum of sound to detect proximity of devices. For example, low level (near) ultrasound can be used to fingerprint places and even be used as an identifier for devices (Peng et al., 2007). Another option is to take advantage of the Doppler effect in sound measurements to detect proximity of objects and potentially people (Malik et al., 2020). The main problem with sound is the difficulty of being captured through the microphone of a phone or other IoT device. Indeed, heterogeneity of microphones influences the accuracy at which sound can be detected by the devices and hence different devices understand the same sound differently.

7.2. Non-Pharmaceutical Interventions (NPIs)

NPIs are non-medical measures that help reduce the spread of any kind of disease. NPIs are essential for prevention and offer the best direct mechanism for countering disease transmission when no medical remedies or vaccines are available (NCEZID and DGMQ, 2020). NPIs can be divided into three categories depending on the target subject of the measure (European Centre for Disease Prevention and Control, 2020): (i) *Individual* – they refer to practicing hand hygiene, respiratory hygiene, use of face masks, and self isolation. (ii) *Environmental* – they consist of cleaning and ventilating indoor or otherwise enclosed spaces. (iii) *Community-based* – they promote social distancing, limited and strict movement, school closures, public event bans, and even complete lockdown.

NPIs are typically combined together to combat the spread of disease. While this can help prevent disease spread more effectively, at the same time it makes it difficult to analyze the effectiveness of each measure individually. As discussed in Section 5.1, effective ventilation and air filtration can help reduce the risk of COVID-19 transmission. Morawska et al. (2020) argue that these, and related environmental and engineering controls, can also improve the effectiveness of NPIs. Specifically, the study recommends 1) reminding facility and building managers to apply suitable engineering controls; 2) enhancing the ventilation effectiveness and the ventilation rates; 3) eliminating indoor air re-circulation and supplying fresh air from outdoors; and 4) using portable air purifiers.

To study the effectiveness of NPIs on COVID-19 transmission, Bo et al. (2020) use information from 190 countries from 23 January to 13 April 2020 and compare four types of NPIs: social distancing, quarantine, restrictions on traffic, and compulsory use of face masks in public. The findings suggest that social distancing is the most effective individual measure, but simultaneously combining two or more NPIs is the most effective overall strategy for limiting COVID-19 infections. Zamir et al. (2020) investigate the optimal control of COVID-19 through NPIs. They narrow down four major NPIs to be effective in reducing the size of a disease outbreak: (i) staying home, (ii) washing hands, (iii) using face mask, and (iv) early detection of cases via PCR tests.

Moreover, the study indicates that if NPIs are not applied, 9 out of 10 susceptible individuals may be infected by COVID-19 within a very short period. Brauner et al. (2020) use a data-driven approach to approximate how NPIs affect the reproduction number and the growth of COVID-19 epidemics in 34 countries in Europe and 7 countries in other continents. They collected chronological data about the NPIs implementation from January to the end of May 2020. The NPIs included closures of businesses, schools and universities, as well as limiting gathering sizes and stay-at-home mandates.

Similarly to the other studies, the findings suggest that applying several NPIs at the same time results in a clearest decrease in the disease transmission and the corresponding reproductive number. Closing universities and schools, mitigating people's crowds and gatherings to less than ten, and stopping face-to-face meetings in businesses each reduced the transmission considerably. While modeling assumptions vary for the exact estimates of effectiveness, the results also show that some NPIs outperformed the others. For instance, stay-at-home was comparatively more effective than other NPIs. Flaxman et al. (2020) explore the effect of major NPIs in eleven countries in Europe from February until early May 2020. The study analyzed five categories of NPIs: social distancing, self isolation, school closures, public event bans, and complete lockdown. The results demonstrate that NPI measures, and in particular a complete lockdown, had a large effect on reducing transmission.

While NPIs are only indirectly related to public transport, their role in minimizing disease transmission risk is essential and in practice NPIs work in tandem with other countermeasures. Understanding the effectiveness and limitations of NPIs helps public transport providers in selecting the best countermeasures based on the current regulations and restrictions, and also provides a context for interpreting the results of studies on individual countermeasures. Indeed, as NPIs are actively used, the effectiveness of any prevention or mitigation measure is always a function of the currently adopted NPIs and the individuals' adherence to follow guidance on their use. From the point-of-view of public transportation operators, the main NPI is social distancing, and controlling passenger densities already prior to the transit event is more effective than any measures that are taken during the event itself. Naturally this results in loss of revenue and a balance between profitability of the transit operations and safety of passengers needs to be established.

8. Discussion

In this survey we have examined scientific literature pertaining to the COVID-19 pandemic and public transport through a disaster management lens, identifying techniques for modeling and understanding risks, and for mitigating and preventing them. We next summarize the key findings and guidelines stemming from the survey and reflect critically on the current scientific understanding to establish a research roadmap for the path forward.

8.1. Key insights

The scientific understanding of the COVID-19 disease and its implications continue to evolve and the appearance of different virus variants further keeps changing and challenging our understanding of the best practices surrounding COVID-19. Nevertheless, there are some general findings that have consistently stood out from the existing studies. Below we summarize the key insights resulting from the works surveyed in this paper

1. There is evidence that traveling in general contributes to the spreading of COVID-19. For example, studies from Wuhan in China showed that infected people carried the virus to other cities (Zheng et al., 2020).
2. While traveling itself has shown strong association with the spread of COVID-19, current scientific evidence suggests that the infection risk during public transit is not elevated – provided that safety measures are followed.
3. Many factors – such as seating configuration, duration of the trip, ventilation, filtration, humidity, social distancing, and mask wearing – affect the transmission risk in public transport. For instance, the transmission risk increases with the co-travel time or while sitting in adjacent seats or in the same row as an infected passenger (Hu et al., 2020). Accordingly, safety recommendations should be strictly followed to minimize risks of infection. Ventilation systems that displace the air vertically (from floor to ceiling, for instance) are more effective at mitigating the infection risks than those that displace the air horizontally (see Section 5.1).
4. Contact tracing apps should be used during travel as they significantly facilitate contacting people at risk of infection. While disease clusters are not frequently linked with public transportation (see Section 5.2), public transportation usage is often interleaved with the activities that result in infections. Hence, the transit events can potentially result in further infections and those at risk are difficult to reach unless automated contact tracing is used.
5. Based on the current scientific understanding, air pollution and dry and cool environmental conditions contribute to the transmission of COVID-19 (Lolli et al., 2020). For instance, a higher number of COVID-19 infections correlates with higher concentrations of air pollutants, such as $PM_{2.5}$,PM_{10}, CO_2, NO_2, and RH. In contrast, temperature, pressure, and the concentration of SO_2, and O_3 have shown a reversed relationship (see Section 3.2).
6. Digital technologies alone cannot combat COVID-19 but can be harnessed to support mitigation and prevention measures, e.g., by monitoring social distancing or automating contact tracing.
7. Complete closure and social distancing control the infection rate in terms of size and subsequent transmission waves. However, a similar effect is produced with strict social distancing measures alone, while restoring people's mobility (Reiner et al., 2020).
8. Social distancing, the use of face masks, and good personal hygiene have shown to provide superior results to mobility restrictions or other non-pharmaceutical interventions (Gakidou and COVID, 2020; Liang et al., 2020).

8.2. COVID-19 safety on transportation systems

The transmission risks in different vehicles are dependent on several factors, with passenger density, typical duration of the trip, and characteristics of ventilation being important considerations. Below we summarize the key recommended mitigation measures for public transport in line with the current scientific understanding.

Recommended social distancing The recommended social distance in many countries remains 2 m (6 feet) apart between individuals. The optimal physical distance depends on the total duration of proximity. For example, a distance of one meter can be sufficient for a trip lasting at most one hour, but even a distance of 2.5 m can be insufficient for a trip taking longer than 2 h. It has been suggested to keep a distance of at least 2 seats within the same row, and to keep the travel time below three hours to minimize the spreading of COVID-19 during the outbreak. It is important to reduce the density of passengers and the number of people sharing the same cabin while traveling. The passengers are recommended to be seated in different rows. If there is a need to arrange the passengers in the same row, they should keep the adjacent seat empty.

Air ventilation and purification Public transport operators are recommended to use ventilation systems that prevent or at least limit the air flow between passengers as this helps to reduce risks of disease transmission. Transit operators are suggested to increase indoor air ventilation and filtration. Inside vehicles, air circulation of 18-times an hour is recommended and air re-circulation should be avoided. During the pandemic, the maintenance of ventilation systems should be intensified. Opening windows for natural ventilation can also be beneficial.

Cleaning surfaces and passengers' personal notes While fomites pose the lowest risk, it is recommended that transport operators clean the seats and surfaces touched by passengers at least once a day with high temperature, especially in overnight sleeping cabins. Passengers must use face masks, and should refrain from shouting or singing and use hand hygiene and sanitiser inside the vehicles and while at the stations.

Mobile applications Passengers are recommended to use smart applications for monitoring their mobility patterns and crowds on different routes. Passengers are advised to use smart reservation systems where possible to reserve a seat in the vehicle in advance. During transit, the use of automated contact tracing apps is highly recommended to allow tracking possible infection chains in case infected patients use the transport at the same time.

8.3. Research roadmap and future outlook

While research literature on the COVID-19 pandemic is continually expanding, there still remain many gaps in the collective scientific understanding that need to be addressed to further improve response against COVID-19. This is particularly critical for the safe operations of different societal functions, including public transportation, as many countries are starting to alleviate restrictions in an attempt to return to normality. Below we critically reflect on the surveyed papers to draw research directions and a roadmap for the path forward.

Model selection Epidemiologic models are important tools that assist policy-makers and health-care practitioners during wide- and fast-spread infectious diseases. Statistical forecasting models (Section 4.2) are usually helpful for near-future predictions. However, they are susceptible not only to the specification of the different compartments (e.g., the S, E, I, and R sub-populations, see Section 4.1), but also to the spreading factor, peak(s) of the infection, and preventive measures put in place by local authorities. Mechanistic models (Section 4.3), can accommodate more complex trajectories and trends of an infectious disease, and potentially provide better predictions over a longer time horizon. For instance, these models can forecast infection cases, hospitalizations, and death given certain intervention assumptions. Despite both models being able to provide insights into the (near-) future course of the disease, their results should always be interpreted within context, especially with regard to the amount and quality of the data upon which the model is built. Determining the best fitting model for a given context remains an open issue. This is particularly challenging in the context of public transit where different regions may have different countermeasures and parameterizations, calling for flexible models that can account for spatial and temporal variations.

Micro-climates inside transportation systems Current scientific understanding suggests that pollutants and meteorological factors play a role in mediating transmission risks. Transportation vehicles with their confined spaces form micro-climates which have different temperature, humidity and pollutant distributions than areas outside them. The concentrations inside vehicles are also affected by the number of passengers inside vehicles, the activities of the passengers, the number of stops, opening and closing of doors at stops and stations and so forth (Motlagh et al., 2021a). The effects of air pollutants on transmission of COVID-19 are mostly studied using governmental databases that contain measurements produced by air quality monitoring stations located outdoors and covering large geographic areas. Fully understanding the transmission risks and mechanisms inside public transport thus needs more studies that compare the distributions of pollutants and meteorological to those found inside vehicles and their carriages.

Ventilation inside the transportation system Ventilation contributes to mitigating the COVID-19 transmission risk, especially for aerosol transmission (SAGE-EMG, 2020). The volume of new air supplied in depends both on the outdoor temperature and the requested indoor temperature as the air conditioning system regulates the indoor air by adapting and mixing the ratio of the recirculated air. A CO_2 sensor can be used to measure air circulation to see whether there is enough fresh air outside getting in and whether the indoor space is filled with potential infectious exhalations. It has been suggested to maintain CO_2 levels below 800 ppm for a duration of below 1 h for indoor environment. Many subways and buses have increased the air circulation rate to be 18 time per hour during the COVID-19 pandemic. Generally it is important to improve the ventilation particularly in densely occupied spaces where the air can quickly become stale and using a fixed circulation rate may not be sufficient. The main effect from ventilation is on aerosol transmissions and thus it alone cannot protect passengers. Indeed, ventilation should work together with other measures (cleaning, air filtration, hand washing, and mask wearing) to minimize the transmission and infection risk. Additional research is needed for the use of CO_2 and other sensors to serve as indicators of the need for ventilation. Indeed, while CO_2 can effectively recognize insufficient ventilation in densely occupied space, the accumulation of CO_2 is much slower in sparsely occupied spaces and other means of monitoring the circulation may be needed.

COVID-19 variants The appearance of new virus variants, such as Alpha (Tang et al., 2020) and Beta (Tegally et al., 2020), is posing new challenges for mitigating risks as these variants may have differing transmission mechanisms or rates, and different severity. For example, both of the aforementioned variants have a mutation (N501Y), which causes increased transmission rate ranging from 40 to 70% (Fontanet et al., 2021). Recently a newer strain of COVID-19, called Delta variant, has spread rapidly and is reported in more than 130 countries globally (World Health Organization, 2021b). The Delta variant is as contagious as chickenpox and may cause severe illness than previous strains in unvaccinated persons and the breakthrough cases for vaccinated people do happen even if it is rare (CDC, 0000). The higher the infection rate, the higher the immunity and vaccination rate are needed to stop the spread and evolution of the virus. While the variants differ from the original virus strain, there are also similarities and thus the same countermeasures can be largely applied to the new variants. Further medical research is needed to fully understand how the different parameters of the variants affect the behavior of the virus and what limitations or advantages different countermeasures have toward different strains of the virus. For example, some variants could potentially survive longer as fomites and thus require better cleaning of surfaces, whereas other variants might call for better ventilation to prevent aerosol transmission. Once these mechanisms are better understood, the guidelines and recommendations for countermeasures in public transportation should be revised and adapted to meet the changes in the behaviors of the different virus strains.

Sensing and AI Sensing technologies have already been useful for tracking and reporting people's mobility and for warning them about crowded places or places that were recently visited by infected people. Fast screening of people at crowded places such as airports has proved crucial at increasing the daily number of screened people while providing fast and reliable results at much lower cost than what laboratory-based testing offers. Nevertheless, there remains significant room for innovative AI and sensor technologies, e.g., to further improve screening and to facilitate higher density traffic.

Mobility Data on human mobility can be utilized to mitigate COVID-19 transmission. Statistics about human mobility have been shown to correlate well with the initial spread of confirmed cases among the cities of China (Ash, 2020), which means that human mobility data can well explain the spatial distribution of COVID-19 cases, at least during the initial starting point (Kraemer et al., 2020). Reductions in human mobility patterns have strong correlation with decreases in confirmed COVID-19 cases and can be used to guide the social distancing to mitigate the COVID-19 transmission. Therefore, it would be useful to examine changes in mobility trajectory patterns resulting from COVID-19. The Levy-walk pattern governing human mobility (Gonzalez et al., 2008) – or at least the parameters governing it – have likely changed due to COVID-19. If the changes can be well understood and modeled accurately, analyzing the effects that mobility has on disease transmission risks can be done more accurately, improving the understanding of mobility control measures in preventing the spread of the pandemic.

CO_2 and other sensors as proxy of COVID-19 transmission risk CO_2 sensors can be used to monitor the COVID-19 transmission risk at indoor and outdoor environments (Kortoçi et al., 2022; Motlagh et al., 2021a). As CO_2 is produced by exhalation at the same time as aerosols containing the SARS-CoV-2 virus, CO_2 can serve as a proxy for the SARS-CoV-2 virus concentrations (Riffi, 2020). However, comprehensive research is needed to have a deeper understanding and to establish the relationship between CO_2 and COVID-19 infection risk. For example, Peng and Jimenez (2020) derive an analytical expression for the probability of COVID-19 aerosol transmission risk in indoor room-level under the situation of eliminating close proximity aerosol and droplet pathways by keeping distance, and excluding transmission caused by fomite and assume a mixed indoor environment. The research shows that the CO_2 level varies in different environments and activities given a fixed infection rate. However, the link between CO_2 and COVID-19 transmission risk is weak due to many factors that can affect each independently. Indeed, factors affecting CO_2 levels do not affect the SARS-CoV-2 virus concentration and vice versa (Eykelbosh, 2021).

9. Summary and conclusion

The COVID-19 pandemic has greatly changed our lives and livelihoods, and this is also the case for public transportation operators. Indeed, the pandemic has resulted in plummeting passenger numbers while at the same requiring transit operators to adopt countermeasures that help ensure the safety of passengers. Having a detailed scientific understanding of the pandemic is critical for decision makers, citizens, and other stakeholders to minimize the impacts on health, economy and society at large. While the collective scientific understanding is rapidly increasing, prior to our work, there has been a limited understanding about the specific risks and mitigation measures related to public transportation. As most transport vehicles comprise confined indoor areas with higher than average density of people, they are generally considered a high risk environment for viral transmission.

We presented a comprehensive and thorough survey that examined the COVID-19 pandemic through the lens of disaster management, offering a survey of the main transmission mechanisms of COVID-19, exploring factors mediating transmission risks, and covering prevention and mitigation strategies that public transport operators can adopt. We also survey and compare different epidemiological models that can be used to predict infection rates, and thus assist decision makers into implementing rules to prevent the spread of the disease. Finally, we also explored mitigation and prevention methodologies for enclosed spaces, including digital, engineering and other non-pharmaceutical countermeasures. The key findings of the survey include: (i) there is evidence to associate public transport with transmission of COVID-19 from a mixture of epidemiological studies and modeling studies; (ii) some of the current research show no association between public transport and risk, especially for trains, where the transmission risk is low; (iii) many factors affect the transmission risk on public transportation, especially sitting locations (distance to the index patient) and duration of the trip; (iv) the air pollution, dry and cool environmental conditions contributes to the transmission of COVID-19; (v) wearing mask, improved ventilation, cleaning, personal hygiene measure, and keep physical distance greatly reduces the transmission risk; (vi) venue closures and restricted mobility benefit only for the limited period of time during which they are in-place; such strategies provide no long-term benefits if not accompanied by social distancing; and (vii) social distancing and good personal hygiene provide superior results to restricted mobility.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors gratefully acknowledge the funding support provided by Academy of Finland, grant numbers 339614 and 324576. This work is also partially supported by the VR group in Finland, the Nokia Center for Advanced Research (NCAR), and Nokia Foundation. The research only reflects the views of the authors.

References

Abuarafah, A.G., Khozium, M.O., AbdRabou, E., 2012. Real-time crowd monitoring using infrared thermal video sequences. J. Am. Sci. 8 (3), 133–140.
Ahangari, S., Chavis, C., Jeihani, M., 2020. Public transit ridership analysis during the COVID-19 pandemic. medRxiv.
Ahmed, N., Michelin, R.A., Xue, W., Ruj, S., Malaney, R., Kanhere, S.S., Seneviratne, A., Hu, W., Janicke, H., Jha, S.K., 2020. A survey of COVID-19 contact tracing apps. IEEE Access 8, 134577–134601.
Alsved, M., Matamis, A., Bohlin, R., Richter, M., Bengtsson, P.-E., Fraenkel, C.-J., Medstrand, P., Löndahl, J., 2020. Exhaled respiratory particles during singing and talking. Aerosol Sci. Technol. 54 (11), 1245–1248.
Anglemyer, A., Moore, T.H., Parker, L., Chambers, T., Grady, A., Chiu, K., Parry, M., Wilczynska, M., Flemyng, E., Bero, L., 2020. Digital contact tracing technologies in epidemics: a rapid review. Cochrane Database Syst. Rev. 8 (8).
Asadi, S., Wexler, A.S., Cappa, C.D., Barreda, S., Bouvier, N.M., Ristenpart, W.D., 2019. Aerosol emission and superemission during human speech increase with voice loudness. Scientific reports 9 (1), 1–10.
Ash, C., 2020. Tracing infection from mobility data. Science.
Aydin, N., Kuşakcı, A.O., Deveci, M., 2022. The impacts of COVID-19 on travel behavior and initial perception of public transport measures in Istanbul. Decis. Anal. J. 2, 100029.
Badr, H.S., Du, H., Marshall, M., Dong, E., Squire, M.M., Gardner, L.M., 2020. Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study. Lancet Infect. Dis. 20 (11), 1247–1254.
Barbieri, D.M., Lou, B., Passavanti, M., Hui, C., Hoff, I., Lessa, D.A., Sikka, G., Chang, K., Gupta, A., Fang, K., et al., 2021. Impact of COVID-19 pandemic on mobility in ten countries and associated perceived risk for all transport modes. PloS ONE 16 (2), e0245886.
Beck, M.J., Hensher, D.A., 2020. Insights into the impact of COVID-19 on household travel and activities in australia–the early days of easing restrictions. Transp. Policy 99, 95–119.
Bertozzi, A.L., Franco, E., Mohler, G., Short, M.B., Sledge, D., 2020. The challenges of modeling and forecasting the spread of COVID-19. Proc. Natl. Acad. Sci. 117 (29), 16732–16738.
Bhagat, R.K., Wykes, M.D., Dalziel, S.B., Linden, P., 2020. Effects of ventilation on the indoor spread of COVID-19. J. Fluid Mech. 903, 1–18.
Bherwani, H., Gupta, A., Anjum, S., Anshul, A., Kumar, R., 2020. Exploring dependence of COVID-19 on environmental factors and spread prediction in India. npj Clim. Atmos. Sci. 3 (1), 1–13.
Biryukov, J., Boydston, J.A., Dunning, R.A., Yeager, J.J., Wood, S., Reese, A.L., Ferris, A., Miller, D., Weaver, W., Zeitouni, N.E., et al., 2020. Increasing temperature and relative humidity accelerates inactivation of SARS-CoV-2 on surfaces. MSphere 5 (4), e00441–20.
Bo, Y., Guo, C., Lin, C., Zeng, Y., Li, H.B., Zhang, Y., Hossain, M.S., Chan, J.W., Yeung, D.W., Kwok, K.O., et al., 2020. Effectiveness of non-pharmaceutical interventions on COVID-19 transmission in 190 countries from 23 january to 13 april 2020. Int. J. Infect. Dis. 102, 247–253.
Bodas, M., Kirsch, T.D., Peleg, K., 2020. Top hazards approach–rethinking the appropriateness of the all-hazards approach in disaster risk management. Int. J. Disaster Risk Reduct. 47, 101559.
Brauner, J.M., Mindermann, S., Sharma, M., Johnston, D., Salvatier, J., Gavenčiak, T., Stephenson, A.B., Leech, G., Altman, G., Mikulik, V., et al., 2020. Inferring the effectiveness of government interventions against COVID-19. Science 371 (6531), eabd9338.
Brodeur, A., Gray, D., Islam, A., Bhuiyan, S., 2021. A literature review of the economics of COVID-19. J. Econ. Surv. 35 (4), 1007–1044.
de Bruin, Y.B., Lequarre, A.-S., McCourt, J., Clevestig, P., Pigazzani, F., Jeddi, M.Z., Colosio, C., Goulart, M., 2020. Initial impacts of global risk mitigation measures taken during the combatting of the COVID-19 pandemic. Saf. Sci. 128, 104773.
Cardwell, K., Jordan, K., Byrne, P., Smith, S.M., Harrington, P., Ryan, M., O'Neill, M., 2021. The effectiveness of non-contact thermal screening as a means of identifying cases of COVID-19: a rapid review of the evidence. Rev. Med. Virol. 31 (4), e2192.
Cartenì, A., Di Francesco, L., Henke, I., Marino, T.V., Falanga, A., 2021. The role of public transport during the second COVID-19 wave in italy. Sustainability 13 (21), 11905.
Carter, L. J., Garner, L. V., Smoot, J. W., Li, Y., Zhou, Q., Saveson, C. J., Sasso, J. M., Gregg, A. C., Soares, D. J., Beskid, T. R., et al., 2020. Assay techniques and test development for COVID-19 diagnosis.
CDC,. Delta variant: What we know about the science. https://www.cdc.gov/coronavirus/2019-ncov/variants/delta-variant.html.
Centers for Disease Control and Prevention, 2021. Scientific Brief: SARS-CoV-2 Transmission. https://www.cdc.gov/coronavirus/2019-ncov/science/science-briefs/sars-cov-2-transmission.html.
Chan, A.B., Liang, Z.-S.J., Vasconcelos, N., 2008. Privacy preserving crowd monitoring: counting people without people models or tracking. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, pp. 1–7.
Chan, L.-S., Cheung, G.T., Lauder, I.J., Kumana, C.R., 2004. Screening for fever by remote-sensing infrared thermographic camera. Journal of travel medicine 11 (5), 273–279.
Cho, H., Ippolito, D., Yu, Y. W., 2020. Contact tracing mobile apps for COVID-19: privacy considerations and related trade-offs. arXiv preprint arXiv:2003.11511.
Chowell, G., Tariq, A., Hyman, J.M., 2019. A novel sub-epidemic modeling framework for short-term forecasting epidemic waves. BMC Med. 17 (1), 164.
Chu, D.K., Akl, E.A., Duda, S., Solo, K., Yaacoub, S., Schünemann, H.J., El-harakeh, A., Bognanni, A., Lotfi, T., Loeb, M., et al., 2020. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis. Lancet 395 (10242), 1973–1987.
Contini, D., Costabile, F., 2020. Does air pollution influence COVID-19 outbreaks?
Copat, C., Cristaldi, A., Fiore, M., Grasso, A., Zuccarello, P., Santo Signorelli, S., Conti, G.O., Ferrante, M., 2020. The role of air pollution (pm and no2) in covid-19 spread and lethality: a systematic review. Environ. Res. 191, 110129.

Cui, Y., Zhang, Z.-F., Froines, J., Zhao, J., Wang, H., Yu, S.-Z., Detels, R., 2003. Air pollution and case fatality of sars in the People's Republic of China: an ecologic study. Environ. Health 2 (1), 1–5.
Dehning, J., Zierenberg, J., Spitzner, F. P., Wibral, M., Neto, J. P., Wilczek, M., Priesemann, V., 2020. Inferring COVID-19 spreading rates and potential change points for case number forecasts. arXiv preprint arXiv:2004.01105 2.
Delamater, P.L., Street, E.J., Leslie, T.F., Yang, Y.T., Jacobsen, K.H., 2019. Complexity of the basic reproduction number (R0). Emerg. Infect. Dis. 25 (1), 1.
Diekmann, O., Heesterbeek, J., 2000. Wiley series in mathematical and computational biology. mathematical epidemiology of infectious diseases: model building, analysis and interpretation.
Domingo, J.L., Marquès, M., Rovira, J., 2020. Influence of airborne transmission of SARS-CoV-2 on COVID-19 pandemic. a review. Environ. Res. 188, 109861.
Dong, D., Tang, Z., Wang, S., Hui, H., Gong, L., Lu, Y., Xue, Z., Liao, H., Chen, F., Yang, F., et al., 2020. The role of imaging in the detection and management of COVID-19: a review. IEEE Rev. Biomed. Eng. 14, 16–29.
Dzien, C., Halder, W., Winner, H., Lechleitner, M., 2021. COVID-19 screening: are forehead temperature measurements during cold outdoor temperatures really helpful? Wien. Klin. Wochenschr. 133 (7), 331–335.
Dzisi, E.K.J., Dei, O.A., 2020. Adherence to social distancing and wearing of masks within public transportation during the COVID 19 pandemic. Transp. Res. Interdiscip. Perspect. 7, 100191.
Eames, K.T., Keeling, M.J., 2003. Contact tracing and disease control. Proc. R. Soc. Lond. Ser. B Biol. Sci. 270 (1533), 2565–2571.
Emenike, H., Dar, F., Liyanage, M., Sharma, R., Zuniga, A., Hoque, M.A., Radeta, M., Nurmi, P., Flores, H., 2021. Characterizing everyday objects using human touch: thermal dissipation as a sensing modality. In: Proceedings IEEE International Conference on Pervasive Computing and Communications (PerCom). IEEE, pp. 1–8.
European Centre for Disease Prevention and Control, 2020. Guidelines for the implementation of non-pharmaceutical interventions against COVID-19. 2020-09-24. https://www.ecdc.europa.eu/en/publications-data/covid-19-guidelines-non-pharmaceutical-interventions.
European Union Agency for Railways, 2021. Travel safety during COVID-19 for passengers travelling long distance by train and other modes. https://www.era.europa.eu/content/study-rail-travel-remains-safer-car-travel-even-during-pandemic_en.
Eykelbosh, A., 2021. Can CO2 sensors be used to assess COVID-19 transmission risk?https://ncceh.ca/content/blog/can-co2-sensors-be-used-assess-covid-19-transmission-risk.
Fanelli, D., Piazza, F., 2020. Analysis and forecast of COVID-19 spreading in China, Italy and France. Chaos Solitons Fractals 134, 109761.
Farrahi, K., Emonet, R., Cebrian, M., 2014. Epidemic contact tracing via communication traces. PloS ONE 9 (5), e95133.
Fattorini, D., Regoli, F., 2020. Role of the chronic air pollution levels in the COVID-19 outbreak risk in Italy. Environ. Pollut. 264, 114732.
Feng, S., Shen, C., Xia, N., Song, W., Fan, M., Cowling, B.J., 2020. Rational use of face masks in the COVID-19 pandemic. Lancet Respir. Med. 8 (5), 434–436.
Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., Parker, M., Bonsall, D., Fraser, C., 2020. Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. Science 368 (6491).
Flaxman, S., Mishra, S., Gandy, A., Unwin, H.J.T., Mellan, T.A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J.W., et al., 2020. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. Nature 584 (7820), 257–261.
Flores, H., Hamberg, J., Li, X., Malmivirta, T., Zuniga, A., Lagerspetz, E., Nurmi, P., 2020. Estimating energy footprint using thermal imaging. GetMob. Mob. Comput. Commun. 23 (3), 5–8.
Fontanet, A., Autran, B., Lina, B., Kieny, M.P., Karim, S.S.A., Sridhar, D., 2021. SARS-CoV-2 variants and ending the COVID-19 pandemic. Lancet 397 (10278), 952–954.
Furuse, Y., Sando, E., Tsuchiya, N., Miyahara, R., Yasuda, I., Ko, Y.K., Saito, M., Morimoto, K., Imamura, T., Shobugawa, Y., et al., 2020. Clusters of coronavirus disease in communities, Japan, January–April 2020. Emerg. Infect. Dis. 26 (9), 2176.
Gakidou, E., COVID, I., 2020. Global projections of potential lives saved from COVID-19 through universal mask use. medRxiv.
Gasser, U., Ienca, M., Scheibner, J., Sleigh, J., Vayena, E., 2020. Digital tools against COVID-19: taxonomy, ethical challenges, and navigation aid. Lancet Digit. Health 2 (8), E425–E434.
Giri, B., Pandey, S., Shrestha, R., Pokharel, K., Ligler, F.S., Neupane, B.B., 2021. Review of analytical performance of COVID-19 detection methods. Anal. Bioanal. Chem. 413 (1), 35–48.
Gkiotsalitis, K., Cats, O., 2021. Public transport planning adaption under the COVID-19 pandemic crisis: literature review of research needs and directions. Transp. Rev. 41 (3), 374–392.
Gonzalez, M.C., Hidalgo, C.A., Barabasi, A.-L., 2008. Understanding individual human mobility patterns. Nature 453 (7196), 779–782.
Gravert, C., Nagl, P., Ball, F., Koerner, T., 2020. Update on SARS-CoV-2 infection risks in long- distance trains. 2020-09. https://www.researchgate.net/publication/344336091_Update_on_SARS-CoV-2_Infection_Risks_in_Long-_distance_Trains.
Guglielmi, G., 2021. Rapid coronavirus tests: a guide for the perplexed. Nature 590 (7845), 202–205.
Hadei, M., Hopke, P.K., Jonidi, A., Shahsavani, A., et al., 2020. A letter about the airborne transmission of SARS-CoV-2 based on the current evidence. Aerosol Air Qual. Res. 20 (5), 911–914.
Hafeez, A., Ahmad, S., Siddqui, S.A., Ahmad, M., Mishra, S., 2020. A review of COVID-19 (coronavirus disease-2019) diagnosis, treatments and prevention. EJMO 4 (2), 116–125.
Harrison, A.G., Lin, T., Wang, P., 2020. Mechanisms of SARS-CoV-2 transmission and pathogenesis. Trends Immunol. 41 (12), 1100–1115.
He, S., Peng, Y., Sun, K., 2020. Seir modeling of the COVID-19 and its dynamics. Nonlinear Dyn. 101 (3), 1667–1680.
Health Protection Surveillance Centre, 2021. Epidemiology of COVID-19 outbreaks/clusters in ireland weekly report. https://www.hpsc.ie/a-z/respiratory/coronavirus/novelcoronavirus/surveillance/covid-19outbreaksclustersinireland/.
Holmdahl, I., Buckee, C., 2020. Wrong but useful-what COVID-19 epidemiologic models can and cannot tell us. N. Engl. J. Med. 383 (4), 303–305.
House, T., Keeling, M.J., 2010. The impact of contact tracing in clustered populations. PLoS Comput. Biol. 6 (3), e1000721.
Hu, M., Lin, H., Wang, J., Xu, C., Tatem, A.J., Meng, B., Zhang, X., Liu, Y., Wang, P., Wu, G., et al., 2020. Risk of Coronavirus Disease 2019 Transmission in Train Passengers: an Epidemiological and Modeling Study. Clin. Infect. Dis. 72 (4), 604–610.
Huang, J., Wang, H., Fan, M., Zhuo, A., Sun, Y., Li, Y., 2020. Understanding the impact of the COVID-19 pandemic on transportation-related behaviors with human mobility data. In: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 3443–3450.
Hunt, M.,. Covid-19 transmission rates on rail, infection risk per passengerjourney: Methodology and derivation of value2021. 2021-01. https://www.rssb.co.uk/what-we-do/the-coronavirus-pandemic-how-we-can-help-you/infection-risks.
IATA, 2020. Low risk of transmission. https://www.iata.org/en/youandiata/travelers/health/low-risk-transmission/.
Jendrny, P., Schulz, C., Twele, F., Meller, S., von Köckritz-Blickwede, M., Osterhaus, A.D.M.E., Ebbers, J., Pilchová, V., Pink, I., Welte, T., et al., 2020. Scent dog identification of samples from COVID-19 patients–a pilot study. BMC Infect. Dis. 20 (1), 1–7.
Jenelius, E., Cebecauer, M., 2020. Impacts of COVID-19 on public transport ridership in Sweden: analysis of ticket validations, sales and passenger counts. Transp. Res. Interdiscip. Perspect. 8, 100242.
Jiang, Y., Wu, X.-J., Guan, Y.-J., 2020. Effect of ambient air pollutants and meteorological variables on COVID-19 incidence. Infect. Control Hosp. Epidemiol. 41, 1011–1015.
Joselow, M., News, E., 2020. There is little evidence that mass transit poses a risk of coronavirus outbreaks. 2020-07-28. https://www.scientificamerican.com/article/there-is-little-evidence-that-mass-transit-poses-a-risk-of-coronavirus-outbreaks/.
Junior, J.C.S.J., Musse, S.R., Jung, C.R., 2010. Crowd analysis using computer vision techniques. IEEE Signal Process. Mag. 27 (5), 66–77.
Kampf, G., Todt, D., Pfaender, S., Steinmann, E., 2020. Persistence of coronaviruses on inanimate surfaces and their inactivation with biocidal agents. J. Hosp. Infect. 104 (3), 246–251.
Katzer, S., 2020. Discussing the CDC and ashrae recommendations for hvac systems. 2020-04-16.
Khanh, N.C., Thai, P.Q., Quach, H.-L., Thi, N.-A.H., Dinh, P.C., Duong, T.N., Mai, L.T.Q., Nghia, N.D., Tu, T.A., Quang, L.N., et al., 2020. Transmission of SARS-CoV 2 during long-haul flight. Emerg. Infect. Dis. 26 (11), 2617.
Klinkenberg, D., Fraser, C., Heesterbeek, H., 2006. The effectiveness of contact tracing in emerging epidemics. PloS ONE 1 (1), e12.

Kortoçi, P., Motlagh, N.H., Zaidan, M.A., Fung, P.L., Varjonen, S., Rebeiro-Hargrave, A., Niemi, J.V., Nurmi, P., Hussein, T., Petäjä, T., et al., 2022. Air pollution exposure monitoring using portable low-cost air quality sensors. Smart Health 23, 100241.
Kraemer, M.U., Yang, C.-H., Gutierrez, B., Wu, C.-H., Klein, B., Pigott, D.M., Du Plessis, L., Faria, N.R., Li, R., Hanage, W.P., et al., 2020. The effect of human mobility and control measures on the COVID-19 epidemic in China. Science 368 (6490), 493–497.
Kretzschmar, M.E., Rozhnova, G., Bootsma, M.C., van Boven, M., van de Wijgert, J.H., Bonten, M.J., 2020. Impact of delays on effectiveness of contact tracing strategies for COVID-19: a modelling study. Lancet Public Health 5 (8), e452–e459.
Leclerc, Q.J., Fuller, N.M., Knight, L.E., Funk, S., Knight, G.M., Group, C.C.-.W., et al., 2020. What settings have been linked to SARS-CoV-2 transmission clusters? Wellcome Open Res. 5 (83), 83.
Lettieri, E., Masella, C., Radaelli, G., 2009. Disaster management: findings from a systematic review. Disaster Prev. Manag. Int. J. 18 (2), 117–136.
Lewis, D., 2020. Is the coronavirus airborne? Experts can't agree. Nature 580 (7802), 175.
Lewis, D., 2021. COVID-19 rarely spreads through surfaces. So why are we still deep cleaning. Nature 590 (7844), 26–28.
Lewnard, J.A., Lo, N.C., 2020. Scientific and ethical basis for social-distancing interventions against COVID-19. Lancet Infect. Dis. 20 (6), 631–633.
Li, M., Zhang, Z., Huang, K., Tan, T., 2008. Estimating the number of people in crowded scenes by mid based foreground segmentation and head-shoulder detection. In: Proceedings of the 19th International Conference on Pattern Recognition. IEEE, pp. 1–4.
Li, Y., Leung, G.M., Tang, J., Yang, X., Chao, C., Lin, J.Z., Lu, J., Nielsen, P.V., Niu, J., Qian, H., et al., 2007. Role of ventilation in airborne transmission of infectious agents in the built environment-a multidisciplinary systematic review. Indoor Air 17 (1), 2–18.
Li, Y., Qian, H., Hang, J., Chen, X., Hong, L., Liang, P., Li, J., Xiao, S., Wei, J., Liu, L., et al., 2020. Evidence for probable aerosol transmission of SARS-CoV-2 in a poorly ventilated restaurant. medRxiv.
Liang, M., Gao, L., Cheng, C., Zhou, Q., Uy, J.P., Heiner, K., Sun, C., 2020. Efficacy of face mask in preventing respiratory virus transmission: a systematic review and meta-analysis. Travel Med. Infect. Dis. 36, 101751.
Lin, S., Wei, D., Sun, Y., Chen, K., Yang, L., Liu, B., Huang, Q., Paoliello, M.M.B., Li, H., Wu, S., 2020. Region-specific air pollutants and meteorological parameters influence COVID-19: a study from mainland china. Ecotoxicol. Environ. Saf. 204, 111035.
Liu, L., Miller, H.J., Scheff, J., 2020. The impacts of COVID-19 pandemic on public transit demand in the United States. PloS ONE 15 (11), e0242476.
Liu, T., Gong, D., Xiao, J., Hu, J., He, G., Rong, Z., Ma, W., 2020. Cluster infections play important roles in the rapid evolution of COVID-19 transmission: a systematic review. Int. J. Infect. Dis. 99, 374–380.
Lolli, S., Chen, Y.-C., Wang, S.-H., Vivone, G., 2020. Impact of meteorological conditions and air pollution on COVID-19 pandemic transmission in Italy. Sci. Rep. 10 (1), 1–15.
Luan, S., Yang, Q., Jiang, Z., Wang, W., 2021. Exploring the impact of COVID-19 on individual's travel mode choice in china. Transp. Policy 106, 271–280.
Luo, K., Lei, Z., Hai, Z., Xiao, S., Rui, J., Yang, H., Jing, X., Wang, H., Xie, Z., Luo, P., et al., 2020. Transmission of SARS-CoV-2 in public transportation vehicles: a case study in Hunan Province, China. In: Open Forum Infectious Diseases, Vol. 7. Oxford University Press US, p. ofaa430.
Maguire, R. S., Hogg, M., Carrie, I. D., Blaney, M., Couturier, A., Longbottom, L., Thomson, J., Thompson, A., Warren, C., Lowe, D. J., 2021. Thermal camera detection of high temperature for mass covid screening. medRxiv.
Malik, A., Mugiri, W.L., Zakwandi, R., Safitri, S., Juliani, T., 2020. Simple experiment of doppler effect using smartphone microfon sensor. J. Penelit. Fis. Aplik. (JPFA) 10 (01), 1–10.
Malmivirta, T., Hamberg, J., Lagerspetz, E., Li, X., Peltonen, E., Flores, H., Nurmi, P., 2019. Hot or not? Robust and accurate continuous thermal imaging on flir cameras. In: Proceedings of the IEEE International Conference on Pervasive Computing and Communications (PerCom. IEEE, pp. 1–9.
Mbuvha, R., Marwala, T., 2020. On data-driven management of the COVIDE-19 outbreak in South Africa. medRxiv.
Morawska, L., Cao, J., 2020. Airborne transmission of sars-cov-2: The world should face the reality. Environ. Int. 139, 105730.
Morawska, L., Tang, J.W., Bahnfleth, W., Bluyssen, P.M., Boerstra, A., Buonanno, G., Cao, J., Dancer, S., Floto, A., Franchimon, F., et al., 2020. How can airborne transmission of covid-19 indoors be minimised? Environment international 142, 105832.
Morley, J., Cowls, J., Taddeo, M., Floridi, L., 2020. Ethical guidelines for COVID-19 tracing apps.
Motlagh, N. H., Toivonen, P., Zaidan, M. A., Lagerspetz, E., Peltonen, E., Gilman, E., Nurmi, P., Tarkoma, S., 2021a. Monitoring social distancing in smart spaces using infrastructure-based sensors. In: Proceedings of the IEEE 7th World Forum on Internet of Things (WF-IoT 2021). IEEE, pp. 1–6.
Motlagh, N.H., Zaidan, M.A., Fung, P.L., Lagerspetz, E., Aula, K., Varjonen, S., Siekkinen, M., Rebeiro-Hargrave, A., Petäjä, T., Matsumi, Y., et al., 2021. Transit pollution exposure monitoring using low-cost wearable sensors. Transp. Res. Part D Transp. Environ. 98, 102981.
Motlagh, N.H., Zaidan, M.A., Lagerspetz, E., Varjonen, S., Toivonen, J., Mineraud, J., Rebeiro-Hargrave, A., Siekkinen, M., Hussein, T., Nurmi, P., et al., 2019. Indoor air quality monitoring using infrastructure-based motion detectors. In: Proceedings of the IEEE 17th International Conference on Industrial Informatics (INDIN), Vol. 1. IEEE, pp. 902–907.
Nations, U., 2020. Finland first in europe to use dogs to detect COVID-19. https://unric.org/en/finland-first-in-europe-to-use-dogs-to-detect-covid-19/.
NCEZID, DGMQ, 2020. Nonpharmaceutical interventions (npis). 2020-04-27. https://www.cdc.gov/nonpharmaceutical-interventions/index.html.
Nguyen, C.T., Saputra, Y.M., Van Huynh, N., Nguyen, N.-T., Khoa, T.V., Tuan, B.M., Nguyen, D.N., Hoang, D.T., Vu, T.X., Dutkiewicz, E., et al., 2020. A comprehensive survey of enabling and emerging technologies for social distancing-part i: Fundamentals and enabling technologies. IEEE Access 8, 153479–153507.
Nguyen, C.T., Saputra, Y.M., Van Huynh, N., Nguyen, N.-T., Khoa, T.V., Tuan, B.M., Nguyen, D.N., Hoang, D.T., Vu, T.X., et al., 2020. A comprehensive survey of enabling and emerging technologies for social distancing-part ii: emerging technologies and open issues. IEEE Access 8, 154209–154236.
Nishiura, H., Oshitani, H., Kobayashi, T., Saito, T., Sunagawa, T., Matsui, T., Wakita, T., COVID, M., Suzuki, M., 2020. Closed environments facilitate secondary transmission of coronavirus disease 2019 (covid-19). MedRxiv.
Nkwayep, C.H., Bowong, S., Tewa, J., Kurths, J., 2020. Short-term forecasts of the COVID-19 pandemic: a study case of cameroon. Chaos Solitons Fractals 140, 110106.
North Carolina Department of Health and Human Services, 2021. COVID-19 clusters in north carolina. https://covid19.ncdhhs.gov/media/725/download?attachment.
Noti, J.D., Blachere, F.M., McMillen, C.M., Lindsley, W.G., Kashon, M.L., Slaughter, D.R., Beezhold, D.H., 2013. High humidity leads to loss of infectious influenza virus from simulated coughs. PloS ONE 8 (2), e57485.
Padhan, R., Prabheesh, K., 2021. The economics of COVID-19 pandemic: a survey. Econ. Anal. Policy 70, 220–237.
Pavlik, J.A., Ludden, I.G., Jacobson, S.H., Sewell, E.C., 2021. Airplane seating assignment problem. Serv. Sci. 13 (1), 1–18.
Peng, C., Shen, G., Zhang, Y., Li, Y., Tan, K., 2007. Beepbeep: a high accuracy acoustic ranging system using cots mobile devices. In: Proceedings of the 5th International Conference on Embedded Networked Sensor Systems, pp. 1–14.
Peng, Z., Jimenez, J. L., 2020. Exhaled CO2 as COVID-19 infection risk proxy for different indoor environments and activities. medRxiv.
Pradhan, D., Biswasroy, P., Naik, P.K., Ghosh, G., Rath, G., 2020. A review of current interventions for COVID-19 prevention. Arch. Med. Res. 51 (5), 363–374.
Prather, K.A., Wang, C.C., Schooley, R.T., 2020. Reducing transmission of SARS-CoV-2. Science 368 (6498), 1422–1424.
Przybylowski, A., Stelmak, S., Suchanek, M., 2021. Mobility behaviour in view of the impact of the COVID-19 pandemic-public transport users in gdansk case study. Sustainability 13 (1), 364.
Putra, S., Mutamar, Z.K., 2019. Estimation of parameters in the sir epidemic model using particle swarm optimization. Am. J. Math. Comput. Model 4, 83–93.
Qi, H., Xiao, S., Shi, R., Ward, M.P., Chen, Y., Tu, W., Su, Q., Wang, W., Wang, X., Zhang, Z., 2020. COVID-19 transmission in mainland china is associated with temperature and humidity: a time-series analysis. Sci. Total Environ. 728, 138778.
Qian, H., Miao, T., Liu, L., Zheng, X., Luo, D., Li, Y., 2021. Indoor transmission of SARS-CoV-2. Indoor Air 31 (3), 639–645.
Rahimi, I., Chen, F., Gandomi, A.H., 2021. A review on COVID-19 forecasting models. Neural Comput. Appl. 30, 1–11.
Ran, J., Zhao, S., Han, L., Chen, D., Yang, Z., Yang, L., Wang, M.H., He, D., 2020. The ambient ozone and COVID-19 transmissibility in China: a data-driven ecological study of 154 cities. J. Infect. 81 (3), e9–e11.
Reiner, R.C., Barber, R.M., Collins, J.K., Zheng, P., Adolph, C., Albright, J., et al., 2020. Modeling COVID-19 scenarios for the United States. Nat. Med. 27, 94–105.
Ribeiro, M.H.D.M., da Silva, R.G., Mariani, V.C., dos Santos Coelho, L., 2020. Short-term forecasting COVID-19 cumulative confirmed cases: perspectives for Brazil. Chaos Solitons Fractals 135, 109853.

Ricciardi, A., Palmer, M.E., Yan, N.D., 2011. Should biological invasions be managed as natural disasters? BioScience 61 (4), 312–317.

Riddell, S., Goldie, S., Hill, A., Eagles, D., Drew, T.W., 2020. The effect of temperature on persistence of SARS-CoV-2 on common surfaces. Virol. J. 17 (1), 1–7.

Riffi, H., 2020. CO2 sensor helps to reduce the risk of COVID-19 transmission indoors. https://www.eetimes.eu/co2-sensor-helps-to-reduce-the-risk-of-covid-19-transmission-indoors/.

Rinta-Homi, M., Motlagh, N.H., Zuniga, A., Flores, H., Nurmi, P., 2021. How low can you go? Performance trade-offs in low-resolution thermal sensors for occupancy detection: a systematic evaluation. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 5 (3), 126.

Roosa, K., Lee, Y., Luo, R., Kirpich, A., Rothenberg, R., Hyman, J., Yan, P., Chowell, G., 2020. Real-time forecasts of the COVID-19 epidemic in China from february 5th to february 24th, 2020. Infect. Dis. Model. 5, 256–263.

Roosa, K., Lee, Y., Luo, R., Kirpich, A., Rothenberg, R., Hyman, J.M., Yan, P., Chowell, G., 2020. Short-term forecasts of the COVID-19 epidemic in Guangdong and Zhejiang, China: February 13–23, 2020. J. Clin. Med. 9 (2), 596.

Rădulescu, A., Williams, C., Cavanagh, K., 2020. Management strategies in a seir-type model of COVID 19 community spread. Sci. Rep. 10 (1), 1–16.

Sacks, J.A., Zehe, E., Redick, C., Bah, A., Cowger, K., Camara, M., Diallo, A., Gigo, A.N.I., Dhillon, R.S., Liu, A., 2015. Introduction of mobile health tools to support Ebola surveillance and contact tracing in guinea. Glob. Health Sci. Pract. 3 (4), 646–659.

Saez, M., Tobias, A., Barceló, M.A., 2020. Effects of long-term exposure to air pollutants on the spatial spread of COVID-19 in Catalonia, Spain. Environ. Res. 191, 110177.

SAGE-EMG, 2020. Role of ventilation in controlling SARS-CoV-2 transmission. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/928720/S0789_EMG_Role_of_Ventilation_in_Controlling_SARS-CoV-2_Transmission.pdf.

Salgotra, R., Gandomi, M., Gandomi, A.H., 2020. Time series analysis and forecast of the COVID-19 pandemic in India using genetic programming. Chaos Solitons Fractals 138, 109945.

Schwartz, S., 2020. Public transit and COVID-19 pandemic: Global research and best practices.

Shakibaei, S., De Jong, G.C., Alpkökin, P., Rashidi, T.H., 2021. Impact of the COVID-19 pandemic on travel behavior in Istanbul: a panel data analysis. Sustain. Cities Soc. 65, 102619.

Shi, F., Wang, J., Shi, J., Wu, Z., Wang, Q., Tang, Z., He, K., Shi, Y., Shen, D., 2020. Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for COVID-19. IEEE Rev. Biomed. Eng. 14, 4–15.

Shinde, G.R., Kalamkar, A.B., Mahalle, P.N., Dey, N., Chaki, J., Hassanien, A.E., 2020. Forecasting models for coronavirus disease (COVID-19): a survey of the state-of-the-art. SN Comput. Sci. 1 (4), 1–15.

Shortall, R., Mouter, N., Van Wee, B., 2022. Covid-19 and transport. a review of factors of relevance to the design of measures and their effects worldwide. Eur. J. Transp. Infrastruct. Res. 22 (1), 118–130.

Siegel, J.D., Rhinehart, E., Jackson, M., Chiarello, L., 2007. 2007 guideline for isolation precautions: preventing transmission of infectious agents in health care settings. Am. J. Infect. Control 35 (10), S65–S164.

Silcott, D., Kinahan, S., Santarpia, J., Silcott, B., Silcott, P., Silcott, B., Distelhorst, S., Herrera, V., Rivera, D., Crown, K., et al., 2020. TRANSCOM/AMC Commercial Aircraft Cabin Aerosol Dispersion tests. National Strategic Research Institute Lincoln United States. Technical Report

Suhaimi, N.F., Jalaludin, J., Latif, M.T., et al., 2020. Demystifying a possible relationship between COVID-19, air quality and meteorological factors: evidence from kuala lumpur, malaysia. Aerosol Air Qual. Res. 20 (7), 1520–1529.

Tang, J.W., Tambyah, P.A., Hui, D.S., 2020. Emergence of a new SARS-CoV-2 variant in the UK. J. Infect. 82 (4), e27–28.

Tegally, H., Wilkinson, E., Giovanetti, M., Iranzadeh, A., Fonseca, V., Giandhari, J., Doolabh, D., Pillay, S., San, E. J., Msomi, N., et al., 2020. Emergence and rapid spread of a new severe acute respiratory syndrome-related coronavirus 2 (SARS-CoV-2) lineage with multiple spike mutations in South Africa. medRxiv.

Tellier, R., Li, Y., Cowling, B.J., Tang, J.W., 2019. Recognition of aerosol transmission of infectious agents: a commentary. BMC Infect. Dis. 19 (1), 101.

Ting, D.S.W., Carin, L., Dzau, V., Wong, T.Y., 2020. Digital technology and COVID-19. Nat. Med. 26 (4), 459–461.

Tirachini, A., Cats, O., 2020. COVID-19 and public transportation: current assessment, prospects, and research needs. J. Public Transp. 22 (1), 1.

UIC, 2020. Contamination rates on trains.

Van Doremalen, N., Bushmaker, T., Morris, D.H., Holbrook, M.G., Gamble, A., Williamson, B.N., Tamin, A., Harcourt, J.L., Thornburg, N.J., Gerber, S.I., et al., 2020. Aerosol and surface stability of SARS-CoV-2 as compared with SARS-CoV-1. N. Engl. J. Med. 382 (16), 1564–1567.

World Health Organization, 2014. Infection Prevention and Control of Epidemic-and Pandemic-Prone Acute Respiratory Infections in Health Care. World Health Organization.

World Health Organization, 2021a. Coronavirus disease (COVID-19): how is it transmitted? https://www.who.int/news-room/q-a-detail/coronavirus-disease-covid-19-how-is-it-transmitted.

World Health Organization, 2021b. COVID-19 vaccines available for all healthcare workers in the Western Pacific Region. https://www.who.int/westernpacific/news/detail/06-08-2021-covid-19-vaccines-available-for-all-healthcare-workers-in-the-western-pacific-region.

Wu, X., Nethery, R. C., Sabath, B. M., Braun, D., Dominici, F., 2020. Exposure to air pollution and COVID-19 mortality in the United States. MedRxiv.

Yuan, X., Yang, C., He, Q., Chen, J., Yu, D., Li, J., Zhai, S., Qin, Z., Du, K., Chu, Z., et al., 2020. Current and perspective diagnostic techniques for COVID-19. ACS Infect. Dis. 6 (8), 1998–2016.

Zamir, M., Shah, Z., Nadeem, F., Memood, A., Alrabaiah, H., Kumam, P., 2020. Non pharmaceutical interventions for optimal control of COVID-19. Comput. Methods Progr. Biomed. 196, 105642.

Zhang, Z., Xue, T., Jin, X., 2020. Effects of meteorological conditions and air pollution on COVID-19 transmission: evidence from 219 Chinese cities. Sci. Total Environ. 741, 140244.

Zhen, J., Chan, C., Schoonees, A., Apatu, E., Thabane, L., Young, T., 2020. Transmission of respiratory viruses when using public ground transport: a rapid review to inform public health recommendations during the COVID-19 pandemic. SAMJ S. Afr. Med. J. 110 (6), 478–483.

Zheng, R., Xu, Y., Wang, W., Ning, G., Bi, Y., 2020. Spatial transmission of COVID-19 via public and private transportation in China. Travel Med. Infect. Dis. 34, 101626.

Zhu, S., Srebric, J., Spengler, J.D., Demokritou, P., 2012. An advanced numerical model for the assessment of airborne transmission of influenza in bus microenvironments. Build. Environ. 47, 67–75.

Zhu, Y., Xie, J., Huang, F., Cao, L., 2020. Association between short-term exposure to air pollution and COVID-19 infection: evidence from China. Sci. Total Environ. 727, 138704.