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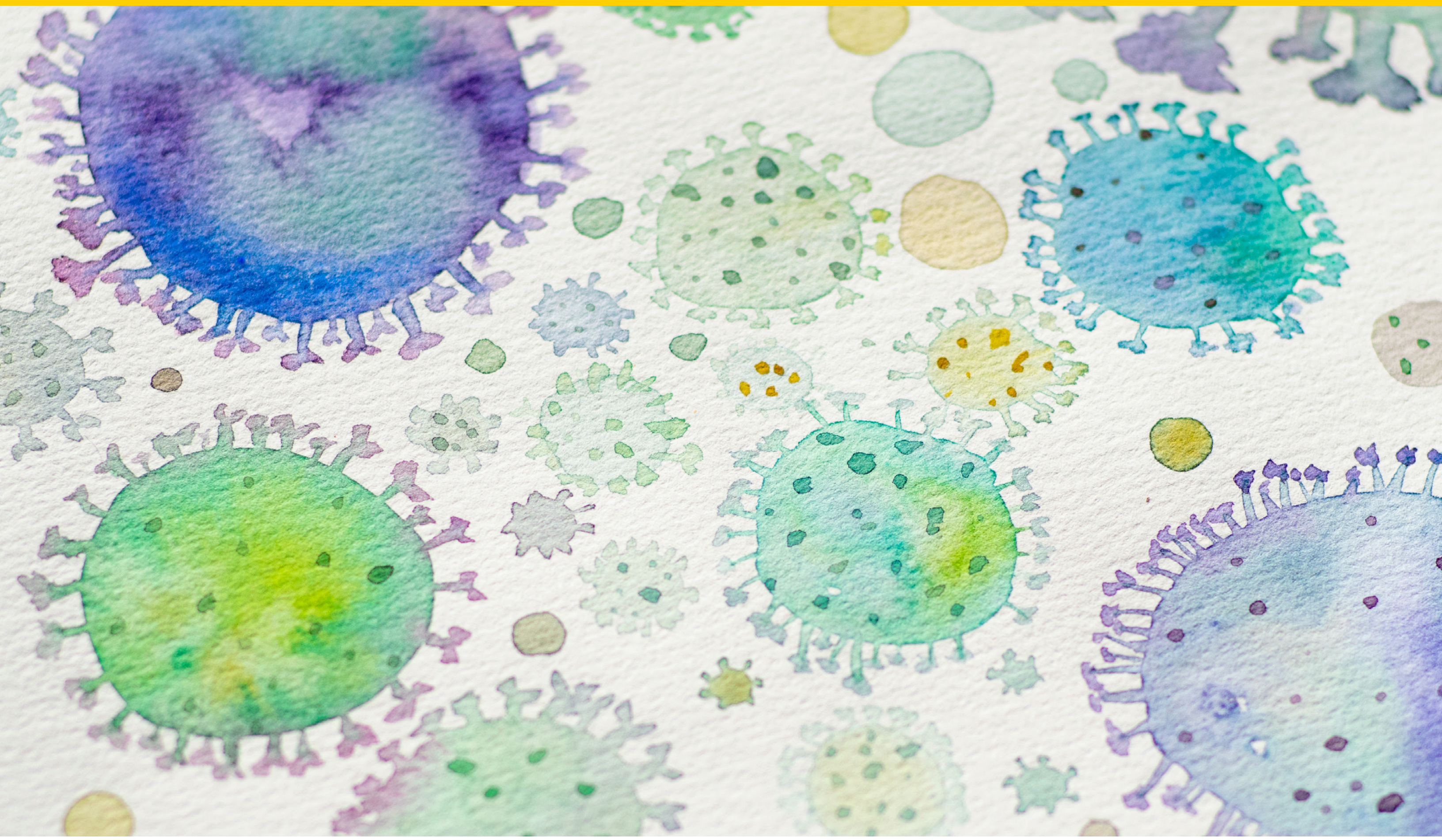

Exploring the Prospective Role of Connected Vehicles in Monitoring and Response to Pandemics and Disasters

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16. Abstract

In the era of connectivity and automation, the prospective vehicular applications of these technologies go beyond transportation operations and traffic management. Connected and automated vehicles (CAVs) are capable of centralized control, information sharing through connectivity, and integrated surveillance. Also, CAVs are readily amenable to innovative design concepts, including disease detection devices in the interior design that could inherently help reduce the propagation of infectious disease. The first chapter of this study attempts to shed light on the operation of CAVs during a pandemic to decrease the infection risk in a community. In this regard, a literature review on the fundamental concepts of epidemiologic modeling is presented, and a population-based epidemic model is proposed to capture the effects of transportation initiatives (including new "modes" such as CAVs) on infection risk disease and propagation. The proposed model can incorporate different transportation modes that have different capacities and disease transmission rates. Next, the report discusses a wide range of disease control policies and interventions that could help minimize the spread of a pandemic. Then the study introduces the features, structure, and operational concept of specially designed CAVs that provide safe and clean mobility services. The prospective efficacy of these special CAVs in controlling a pandemic is investigated using the proposed epidemiologic model, and this is demonstrated using a synthetic transportation network in the specific context of the COVID-19 pandemic. With CAV ability to operate without a human driver, there is one less person in the vehicle, thereby reducing infection risk. Also, CAVs could be leveraged for contact-free delivery of goods and services during periods of lockdown or quarantine, thereby minimizing person-to-person contact. The study then proposes an evaluation methodology and several metrics that could be used by transportation and health agencies to assess the effectiveness of CAV-related pandemic control interventions. The second part of the study discusses prospective applications of vehicle connectivity and automation in managing disaster events. The report presents a synthesis of literature on this subject, identifies the various types of disasters and stages of infrastructure system disruption thereof, and presents ways to leverage CAV capabilities at each stage not only to build infrastructure resilience but also to serve populations during such events. In sum, this study shows that CAVs can potentially assist in monitoring and responding to pandemics and disasters, and therefore, hold promise for enhancing preparedness and resilience in such crises in the future.

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ABM	Agent-based Modeling
CAV	Connected and Autonomous Vehicle
CTNH	Critical Transportation Need Households
CDC	Center for Disease Control
EMA	Emergency Management Agency
HDV	Human-Driven Vehicle
HEPA	High-Efficiency Particulate Air (filter)
IBM	Individual based Model
IOO	Infrastructure Owner or Operator
MOE	Measure of Effectiveness
MCM	Mathematical Compartment Model
NPI	Non-Pharmaceutical Interventions
OD	Origin-destination Pair
OEM	Original Equipment Manufacturer
PBM	Population based Model
PMI	Pandemic Mitigation Intervention
RRPD	Reduction in the Rate of Performance Deterioration
SARS	Severe Acute Respiratory Syndrome
SEIR	Susceptible, Exposed, Infected, and Recovered
SIS	Susceptible Infectious Susceptible
SPI	System Performance Indicator
ULPA	Ultra-Low Particulate Air (filter)
UV	Ultraviolet
V2I	Vehicle to Infrastructure

CHAPTER 1 GENERAL INTRODUCTION

1.1 Study Background

1.1.1 Pandemics

Four distinct influenza pandemics have occurred in recent history (the 1918-19 Spanish flu, the 1956-1959 Asian flu, the 1968-1970 Hong Kong flu, and the 2002-2004 SARS-CoV-1 coronavirus). Combined, these four pandemics were responsible for over 100 million deaths and immeasurable social and economic impact in several hundreds of billions of dollars. Great progress has been made in influenza detection over the past century (Viboud et al., 2003; Hirose, et al., 2012; Molaei et al. 2019). Yet still, over the past decade, researchers and health care professionals have cautioned that the emergence of a new strain of influenza can be extremely problematic (CDC, 2019). Such realization became painfully manifest in 2020 as the COVID-19 (a respiratory disease caused by the SARS-CoV-2 coronavirus) unfolded (Wu et al., 2020). In Spring 2020, the World Health Organization (WHO) declared COVID-19 as a pandemic. At the time of writing, there has been 772 million confirmed cases and more than 6 million deaths recorded worldwide (WHO, 2023), and the global health, societal and economic effects of this virus continue to grow. The U.S. Congressional Budget Office has projected that the COVID-19 pandemic is inflicting a devastating long-term blow to the U.S. economy, costing $7.9 trillion over the next decade (CBO, 2020). At the time of writing, the COVID-19 pandemic has waned. At its peak in the U.S., the daily number of fatalities exceeded 2,000.

The COVID-19 impact could be worse if the disease spread is not monitored and controlled. Governments worldwide therefore desperately seek to identify and evaluate policies and technologies that can help monitor the pandemic progression and to make recommendations to reduce the spread. According to the World Health Organization (WHO, 2020), regular monitoring and sharing of quality of pandemic data allow governments and agencies to:

- describe pandemic epidemiology features (risk groups, transmission characteristics, and impact),
- provide jurisdictions and health agencies information on pandemic transmission in various locations, which allows the agencies to make better preparations for upcoming surges, and
- monitor spatial and temporal trends in the pandemic transmission.

Besides COVID-19, a succession of regional and global infectious disease outbreaks in recent decades has generated an increasing interest in real-time epidemic trend projections to help control such diseases. Enhancements in the state of the art, which includes the development of mechanistic transmission models, have been propelled by four drivers: higher levels of epidemiological data generation and availability; innovative platforms and streams for data collection including social media and search engines (Althouse et al, 2015; Bansal et al., 2016); the rise of machine learning and sophisticated statistical approaches (Ginsberg et al., 2009; Shaman et al., 2012); and computational advances (Chretien et al., 2015). In these areas, the research terrain is fast changing. For example, modelers continue to develop innovative tracking models and algorithms to facilitate reliable predictions of pandemic trajectory (Viboud and Vespignani, 2019).

In a recent article in the Nature journal, Holmes et al. (2018) urged infectious disease experts to focus on proactive, real-time surveillance of human populations, which they asserted is a more cost-effective and simpler way to mitigate disease outbreaks. Governments at all levels often resort to the use of surveillance tools to help fight disease outbreaks, and in recent times, smartphone mobile networks have proven to be effective at carrying out such surveillance. In the literature, it is observed that a common thread in the application of monitoring technologies is that they identify the locations and movements of infected people and monitor quarantines. Singapore's *TraceTogether* app used cellphone Bluetooth signals to ascertain the extent of contact between uninfected people and potential carriers of the virus. In Hong Kong, health authorities monitored resident's movements and were alerted anytime a potential and known carrier exited a quarantine zone. In South Korea, the authorities used smartphone location data, CCTV video feed and credit card transactions, to track confirmed cases. In Israel, cell phone-based locations of residents were used to track the movement of infected persons. At several cities in India, after infected persons were identified, airline and train reservation data were monitored to identify and prevent them from traveling.

At the time of writing, the COVID-19 pandemic has waned. However, several countries continue to take precautions and are studying the effectiveness of past interventions (including digital technologies) as well as building new arsenals to combat any future outbreaks. It has been cautioned that digital technologies do not represent a silver bullet. Yest still, there seems to exist general agreement among researchers and practitioners that the technologies have a key role to play in comprehensive pandemic monitoring and control, and that they could complement existing conventional public-health measures to reduce the human and economic impact of COVID-19.

1.1.2 Disasters

Transportation facilities are prone to disruption due to natural or manmade disasters including terrorist attacks (such as 9/11), hurricanes (such as Sandy, New York City, 2012). The toll of such events is often enormous in terms of financial cost and human suffering. In past work, researchers have hypothesized that such adversities could be minimized if adequate and reliable information could be exchanged between the residents (such as road users) and the government authorities (such as transport agencies). Opportunities to address disasters could occur at three phases of the disaster life cycle: (i) pre-event, (ii) response, and (iii) recovery. The response phase initiates after the onset of disruptive event. In disaster events, the transportation agency may need to implement evacuation processes to save human life and to improve the transportation network performance depending on the type of disruption. The former depends on the traffic management strategies (such as route guidance for CAVs through V2I, dynamic resource allocation, medical service distribution and emergency rescue), and the latter depends on both traffic management strategy and the short-term transportation infrastructure projects with duration of few hours to few days, such as repair of damaged road assets including roadside units, and debris removal.

The emergence of CAVs could have a dichotomous effect during the response phase. The advantage is related to the capability of CAVs to provide real-time exchange of information between transportation agency and travelers. This could help smoothen evacuation and reduce fatalities. On the other hand, the issues of cyber-attacks and malicious feeding of erroneous information to CAVs could increase traffic congestion which may delay the evacuation process. Specifically, during this phase, transportation facilities often experience extreme and unusual travel demands. This situation underscores the need to provide real-time travel time information to the residents and travelers.

1.2 Problem Statement and Study Objectives

This report seeks two main objectives: (i) assessing the benefits of CAVs in controlling a pandemic and (ii) identifying the potential of using CAVs to facilitate natural disaster evacuation. The first part of the report focuses on the first objective of the study, covers pandemic monitoring, and examines how CAVs could provide a safe transportation mode in a pandemic. In this regard, this study reviews the existing epidemic models, especially the ones that focus on transportation systems. Then, this study tries to develop a framework to assess the effectiveness of pandemic-control policies and the roles of transportation modes in spreading diseases. Moreover, this report identifies and proposes strategies that could decrease the risk of infection in vehicles and other transportation modes. The research explores how a CAV fleet, through dynamic and collaborative trip planning and route selection, could help reduce human contact and exposure during pandemics. Furthermore, the efficacy of the CAV fleet in mitigating a pandemic is assessed by applying the proposed framework of this study.

The second part of the research focuses on the second objective of this study and addresses the potential of using CAVs to facilitate natural disaster evacuation. During such events, the connectivity features of CAVs could help enhance information exchange among the transportation agency, road users, the general public, and particularly, evacuees. In this regard, this study presents a synthesis of literature and discusses various stages of disasters and their disruptions to infrastructure systems. Then, the study identifies and presents different ways and strategies that CAVs can potentially be used to serve society during disasters.

1.3 Study Approach

The first part of the study is designed to address how the technologies of vehicle automation and connectivity could be leveraged during a pandemic to decrease the infection risk in a community. For this, a literature review on the fundamental concepts of epidemiologic modeling is studied, and a population-based epidemic model is developed to capture the effects of transportation initiatives (including new "modes" such as CAVs) on infection risk disease and propagation. A model is proposed that incorporates different transportation modes that have different capacities and disease transmission rates. The study then identifies disease control policies and interventions that could help minimize the spread of a pandemic, and how the features, structure, and operational concept of a specially designed CAV could provide safe and clean mobility services. The prospective efficacy of these special CAVs in controlling a pandemic is investigated using the proposed epidemiologic model, and this is demonstrated using a synthetic transportation network in the specific context of the COVID-19 pandemic. The study then proposes several metrics for assessing the effectiveness of transportation-related pandemic control policies and interventions. The second part of the report discusses the prospective applications of vehicle connectivity and automation in managing disaster events. First, a synthesis of relevant literature on this subject is presented, disaster types are identified, and the various stages of infrastructure system disruption during a disaster, are discussed. The study identifies ways to leverage CAVs not only to build infrastructure resilience but also to serve populations during disasters.

This report is organized as follows: Chapter 1 presents an overall introduction to the study. Part I addresses CAVs and pandemics and includes a review of the literature (Chapter 2), epidemic modeling (Chapter 3), CAV designs that foster safe mobility in a pandemic (Chapter 4), control policies and interventions during a pandemic (Chapter 5), and the effectiveness measurement of pandemic mitigation interventions (Chapter 6). Chapter 7 concludes Part I of the study. Part II addresses CAV and disasters and consists of discussions on the prospective role of CAVS in disaster management (Chapter 8). Part III contains the closing chapters: the summary of study effort (Chapter 9), a synopsis of the USDOT performance indicators (Chapter 10), and the study outcomes and outputs are presented (Chapter 11).

Part I:
CAVs and Pandemics

CHAPTER 2 REVIEW OF THE LITERATURE

2.1 Introduction

In this era of increasing connectivity and automation, the potential uses of Connected and Autonomous Vehicles (CAVs) extend far beyond transportation and traffic management. For example, at the start of the COVID-19 pandemic, the significant role these vehicles could play in pandemic monitoring and response became apparent. Mobile sensors could be made to collect data in real time, providing valuable insights into epidemic dynamics, and helping in the implementation of effective response strategies.

This chapter presents a review of literature on the utilization of CAVs in this innovative manner. The review is structured into two main sections: (1) Epidemic Dynamics and (2) Epidemic Modeling in the context of transportation systems. The first section addresses a broad range of studies on disease transmission and the characteristics that define the spread of infectious diseases including COVID-19. This understanding is pivotal in shaping how CAVs might be utilized to monitor and respond to pandemics. The second section surveys existing models used to predict and analyze the spread of infectious diseases, particularly within the context of transportation networks. The insights from these models are essential for integrating CAVs into public health response.

This literature review hopefully serves as a basis for establishing a theoretical framework for prospective application of CAVs in pandemic management. Understanding epidemic dynamics and the principles governing the spread of infectious diseases is essential for effective pandemic response and management. The case of COVID-19 serves as a prime example for illustrating these dynamics as the disease's transmission characteristics have spurred extensive research and led to innovative methodologies in modelling epidemic spread.

2.2 Epidemic Dynamics

2.2.1 Epidemiological Evidence of Pandemics and Response Strategies

It is well known that COVID-19 is highly contagious and can spread rapidly. In epidemiological taxonomy, a reproduction number, R_0, is defined as the average number of people (in a susceptible population) to whom an infected person could transmit a virus). In the case of COVID-19, R_0 is estimated to range from 2.0 to 3.0 (Li et al., 2020). The significance of this high transmission rate lies in its impact on public health interventions and strategies designed to curb the spread. The transmission dynamics of COVID-19 are influenced by several key factors, including the incubation period of the virus, its infectious period, the presence of asymptomatic carriers, and the occurrence of super-spreading events. On average, the incubation period spans approximately 5-6 days, with an upper limit extending up to 14 days, while the infectious period can begin 2-3 days before symptoms appear and last up to 10 days after (He et al., 2020). This prolonged and pre-symptomatic infectious period highlights the challenge in controlling the spread of the virus, as it allows for a high potential of unseen transmission. Another aspect of COVID-19's epidemiology is the role of asymptomatic carriers in the spread of the virus. As of late 2020, estimates indicated that between 20-40% of COVID-19 cases might be asymptomatic, yet still capable of transmission

(Oran and Topol, 2020). This information greatly complicates early response strategies and highlights the need for widespread and frequent testing even in populations with few visible symptoms. The COVID-19 pandemic was also characterized by several super-spreading events. In these instances, a small number of individuals infected many people (Adam et al., 2020). The occurrence of these events indicates a high heterogeneity in the transmission of the virus which dramatically impacts the dynamics of the epidemic and influences the design and implementation of control measures.

Dietz and Black (2012) and Dietz et al. (2018) discussed pandemic planning initiatives and control mechanisms. During the COVID-19 pandemic, several non-pharmaceutical interventions (NPIs) were deployed globally. These included social distancing, systematic testing, mask-wearing, contact tracing, quarantining of suspected cases, and large-scale lockdowns (Ferguson et al., 2020). The effectiveness of these interventions varied widely, demonstrating the importance of context-specific strategies in combating a pandemic. Different nations experienced varying degrees of success with different response strategies. For example, countries like New Zealand and Australia successfully eliminated local transmission of the virus through strict lockdowns (Baker, et al., 2020). Conversely, Sweden, which initially avoided lockdowns and aimed for herd immunity, saw higher infection and death rates (Ludvigsson, 2020). These contrasting outcomes provide valuable lessons for future pandemic responses. From a pharmaceutical perspective, the development and distribution of effective vaccines represented a key landmark in the fight against COVID-19, and this pharmaceutical intervention greatly reduced the severity of the disease, slowed transmission (Thomas et al., 2021), and lowered the travel-related risks of infection.

Transportation activities have been identified as significant contributors to the spread of transmittable disease (Wilson, 1995; Sinha and Labi, 2007; National Academies of Sciences, Engineering, and Medicine 2008, 2017, 2021, 2022; Wesolowski et al. 2016). This is largely due to the enclosed environment in vehicles, the difficulty of maintaining social distancing, and the high frequency of interpersonal contact in public transport systems, which facilitate virus transmission (Tian et al., 2020). For example, early super-spreading events were linked to cruise ships where close quarters and shared facilities created an environment conducive to the rapid spread of the virus (Rocklöv et al., 2020). Similarly, research has suggested that air travel facilitated the global spread of COVID-19 because flight routes were found to correspond to patterns of international transmission (Bogoch et al., 2020). In response to these challenges, various strategies were implemented to reduce transmission in transportation contexts. These included enhanced sanitation protocols, the enforcement of mask-wearing in public transportation, physical distancing measures, and vehicle capacity reduction (Hua and Shaw, 2020). Moreover, international travel restrictions, including flight bans and mandatory quarantine periods for incoming travelers, were implemented to control cross-border transmission (Chinazzi et al., 2020). Also, technology played a pivotal role in the mitigation. For example, digital contact tracing apps were used in several countries to identify and notify individuals who had been in close contact with confirmed cases, and this was often effective in curtailing transmission (Ferretti et al., 2020).

In the specific context of CAVs, they have shown potential to contribute to pandemic responses. With AVs' ability to operate without a human driver, there is one less person in the vehicle, thereby potentially reducing infection risk. In addition, AVs could also be leveraged for contact-free delivery of goods and services during periods of lockdown or quarantine, thereby minimizing person-to-person contact (van Zandvoort et al., 2020).

2.2.2 Epidemic Modeling

Modeling can help describe the propagation characteristics of epidemics and ultimately facilitate the formulation of efficacious strategies for containment and mitigation. They provide a framework for approximating complex real-world systems, enabling a systematic exploration of the overall social system behavior under various circumstances. Models can be developed to simulate hypothetical scenarios and examine the consequences of different strategic or tactical interventions for pandemic management.

Epidemic modeling techniques can be categorized as follows: objective, resolution, and the technique deployed. Each category provides unique insight into the dynamics of disease propagation.

- **Modeling objective**: the objectives of these models span a spectrum from descriptive to predictive to prescriptive, each serving a unique role in epidemic management.
- **Resolution**: the resolution of a model determines the granularity of the data needed for the model, from coarse-grained (population-based) to fine-grained (individual-based), and the specificity of the results.
- **Technique**: these include statistical models, mathematical compartment models, network-based models, or agent-based models, dictate the methodological and mathematical approaches to be applied.

Regarding the model objective, distinct objectives delineate the types of models used to tackle the complexities of disease spread Within the diverse landscape of epidemiological modeling. Descriptive models serve as the cornerstone for characterizing the fundamental mechanics of an epidemic, mapping transmission pathways, and calibrating essential epidemiological parameters (Hethcote, 2000). By capturing these foundational dynamics, descriptive models contribute significantly to understanding the past patterns and trends of epidemics. On the other hand, predictive models act as a forward-looking tool, projecting the future trajectory of a disease based on extant data and assumptions intrinsic to the disease (Bonabeau, 2002). Such forecasts are invaluable to prescriptive analysis such as strategic planning. This includes preparing for hospital capacities and designing health resource allocation. Finally, prescriptive models establish specific intervention strategies including pharmaceutical and non-pharmaceutical interventions to curtail the disease spread. Prescriptive models typically incorporate optimization algorithms to identify the most cost-effective and efficient courses of action, thereby providing recommendations for managing the epidemic (Al Qundus et al., 2023). Together, these three categories of models offer a robust and multifaceted approach to comprehension, forecast, and response to epidemics.

Model resolution significantly impacts the model function and application. At one end of the spectrum, population-based models (PBM) operate under the assumption that the population is a homogeneous entity and, therefore uses averages of the characteristics of the individuals within it, as stated in the classic piece by Kermack and McKendrick (1927). A prime example of this is the Susceptible-Exposed-Infectious-Recovered (SEIR) compartmental model widely used in epidemiology due to its effective simplification of complex disease dynamics. In contrast to this approach, individual-based models (IBM) acknowledge the heterogeneity and idiosyncrasies of individuals and their interactions (Grimm et al., 2020). Network-based and agent-based and models are subcategories of this model type, offering a nuanced lens to capture intricate interactions and behaviors that can impact disease spread. These divergent approaches offer unique insights, and used in conjunction with each other, they provide a more comprehensive understanding of disease transmission.

Regarding the techniques applied in epidemiological modeling, there is a wide range of methodologies, each with its merits and demerits. First, statistical models leverage statistical methods to align models with actual data, deciphering correlations, and establishing relationships in the process. These models often find utility in the initial stages of an outbreak, providing essential estimates of key parameters (Vynnycky and White, 2010; Pastor-Satorras et al., 2015). Secondly, Mathematical Compartment Models place segments of the population into “compartments” based on their infection status, such as susceptible, exposed, infectious, or recovered. This technique uses differential equations to depict the transitions between compartments, thereby developing disease trajectories (Diekmann et al., 2013). On the other hand, network-based models conceptualize individuals as nodes and their interactions as edges within a network. This approach excels in capturing heterogeneity in individual interactions and is particularly instrumental when dealing with super-spreading events (Pastor-Satorras et al., 2015). Lastly, Agent-based Models simulate the actions and interactions of autonomous entities or “agents,” seeking to evaluate the collective impact of individual actions on the system. The advantage of agent-based models is that they can encapsulate more complex and realistic behaviors compared to compartmental models, allowing for nuanced comprehension of the disease dynamics (Macal and North, 2005).

The epidemic dynamics model types, each with their distinct characteristics and applications, help in understanding patterns and predicting trends, and thereby, responding effectively to infectious disease outbreaks. As discussed in earlier paragraphs, descriptive, predictive, and prescriptive models serve different yet interconnected objectives that facilitate a comprehensive approach to epidemiological studies. Furthermore, both population-based and individual-based models offer valuable perspectives, capturing different levels of complexity and heterogeneity inherent in disease transmission. The choice of technique—whether statistical, mathematical compartment, network-based, or agent-based—depends largely on the specifics of the disease, population, and epidemiological objectives at hand.

The prospect of integrating Connected and Autonomous Vehicles (CAVs) into these modeling frameworks opens exciting new avenues for epidemic monitoring and control. With their ability to collect and transmit real-time data, CAVs have the potential to greatly enhance the precision and timeliness of epidemiological data used in these models. This could revolutionize how predictive and prescriptive models are used, allowing for real-time predictions and responses to changes in epidemic dynamics. Moreover, the detailed individual-level data captured by CAVs could provide a significant boost to individual-based and agent-based modelling, enabling a deeper understanding of disease transmission dynamics within and between communities. During pandemics, AVs that have no human operators eliminate the possibility of direct driver-to-passenger and passenger-to-driver infection, thereby helping to reduce the spread of disease. In the current post-pandemic era, there still exist vestiges of the diseases and transmission is still possible particularly because mask wearing has become rare. As such, it is prudent for vulnerable populations to exercise caution. Figure 2.1 presents an example of autonomous vehicle operations in 2022 in Phoenix. As there is no driver, the risk of infection to or from the passenger to other passengers that use the vehicle subsequently, is reduced significantly.

Figure 2.1 In a pandemic, AVs could help reduce disease spread by eliminating direct driver-to-passenger and passenger-to-driver infection *(Source: Matt York, AP Photo)*

2.3 Epidemic Modeling in the Context of Transportation Systems

In a pandemic situation, vehicles of the transportation modes, particularly, public transit, could constitute primary agent of disease transmission. This is because of the close contact of travelers in transportation vehicles coupled with quick access to locations around the world. Therefore, it is critical to control the disease's spread at transportation hubs. Epidemic modeling helps to do this. As stated in an earlier section of this chapter, these models help provide insight into not only disease propagation dynamics, but also, the roles of catalytic and inhibiting media and the effectiveness of alternative interventions and control policies in the context of such media. This section reviews the studies that addressed transportation-related factors in epidemic modeling. Similar to the granular models discussed in an earlier section, transport-related epidemic models can be categorized as: population-based and individual-based models.

In population-based models, the entire population is considered one single group (or entity). In this approach, it is assumed that there is very little difference between the individuals in each group. In other words, the characteristics, and behaviors of the individuals within each group are homogenous. In cases where the characteristics and behavior of the individuals in a community are considerably different, such homogeneity assumption is not valid. As such, the community is divided into homogenous subgroups that interact with each other (Chowell et al., 2016).

In the context of measles epidemic dynamics, Sattenspiel and Dietz (1995) presented an SIR compartment model that incorporated mobility activities. They distributed the population into regions and captured the travel dynamics of travelers between the regions. Subsequently, Arino and van den Driessche (2003) introduced an epidemic model that accounted for inter-city travel. In this model, they considered two compartments (susceptible and infected) and presented a SIS model to capture the disease propagation. Hufnagel et al. (2004) focused on the global SARS pandemic and introduced a stochastic SIR model to forecast the geographical spread of epidemics. They simulated the global propagation of SARS through air travel and investigated different mitigation and control strategies (Hufnagel et al., 2004). Colizza et al. (2006) developed a stochastic SIR model to forecast global epidemics by considering worldwide air travel. Cui et al. (2006) developed a SIR model to capture the SARS disease propagation between different cities or regions. Liu and Takeuchi (2006) developed a SIQS model to study transportation factors, travel restrictions, and entry and exit screening in a SARS pandemic (Liu and Takeuchi, 2006). In another study, Xu et al. (2013) adopted an SIR model to study the dispersion of a disease over multiple cities or areas through transportation systems. Furthermore, they examined the efficacy of public health policies including discouraging needless trips and regular disinfection of transit vehicles. Denphedtnong et al. (2013) developed a SEIRS model to analyze the effect of transportation-related factors on SARS spread between two cities.

More recently, Li (2020) proposed a simulator for epidemic propagation in China. In their simulator, a SEIR model was implemented to predict the spread of disease in different cities. Then, incorporating the public transportation systems into the simulation through a multi-layer network (where each layer represented each mode of transport), they applied this simulator to track the daily pattern of COVID-19 pandemic dispersion over several cities in China. Hoover et al. (2021) proposed a framework to decrease the susceptibility of transit riders to the COVID-19 pandemic by changing the operational routes of public transit. They formulated this framework as a multi-objective optimization problem that maximizes transit ridership and minimizes the spread of COVID-19 in the network. Zewdie and Gakkhar (2022) evaluated the effectiveness of quarantine and awareness strategies in pandemic mitigation by incorporating a new compartment (aware and quarantined) into the epidemic model. Also, they studied the effects of transportation hub entry and departure screening on the spread of a disease. Zhu and Guo (2021) assessed the transportation suspension policy during the COVID-19 pandemic by developing a set of linear regression models. They considered the suspension of two major transportation systems (high-speed rail and air), and showed that the transportation suspension was effective in controlling the COVID-19 pandemic. Qian and Ukkusuri (2021) adopted a SEIR model that examined the role of transportation in disease dispersion and developed an optimal control policy for public transportation systems.

Kuehn and Mölter (2022) introduced a multiplex network model to incorporate the disease's dynamic and mobility patterns of diseases. The epidemic modeling part was based on a SIRS framework, and the presented network for mobility consists of a static layer and a dynamic layer. They analyzed the disease-free and endemic equilibrium states of the model. Liu et al. (2022) evaluated the efficacy of Singapore’s pandemic control policies during the COVID-19 pandemic. They incorporated the transportation systems into a SEIR model to capture the disease spread in activity zones and travel modes and compared different control policies and their effectiveness.

Thomas et al. (2022) studied the relationship between mass transit ridership and the spread of COVID-19 in large cities in the US, using a statistical model based on national transit adoption surveys and the number of confirmed COVID-19 cases. They concluded that there existed a strong correlation between mass ridership and the number of confirmed cases. Yao et al. (2022) explored the impact of COVID-19 on taxi travel in Ningbo, China, from both demand and supply perspectives. They quantitatively compared taxi travel characteristics and taxi industry operations before and after the epidemic. Using an SIR model and taxi travel simulations, and they analyzed demand and supply changes under various intervention scenarios like lockdown and restricted travel policies, and identified the factors that caused taxi travel decline during the pandemic. Calatayud et al. (2022) studied the role of the freight network in spreading COVID-19 in Colombia. They showed that freight transport has a great potential to spread the disease through freight hubs.

Individual-based models (IBMs) and agent-based models (ABMs) address interactions between individuals or specified groups of individuals, accounting for the differences in behaviors and risks among the entities. In recent times, this class of models has become increasingly popular for studying infectious disease dynamics, because of higher levels of methodological rigor, computational power, and data availability (Chowell et al., 2016). ABMs typically are data intensive as they seek to replicate multi-faceted behaviors of each individual of small group of individuals and help model dynamic network attributes and cross-agent disease transmission. Rakowski et al. (2010)'s agent-based model analyzed the dispersion of an influenza epidemic in Poland. This agent-based model incorporated a stochastic simulation environment that predicted the disease propagation and the travelers' mobility in both urban and rural areas. Zhou et al. (2012)'s agent-based model simulated the role of public transit systems in spreading a pandemic. Similarly, Zhang et al. (2015) investigated the roles of public transit systems (subway and bus) in influenza propagation and examined the related control policies in such pandemics. Their agent-based model used a microscopic representation of public transit system and was demonstrated using an influenza case study.

CHAPTER 3. EPIDEMIC MODELING

3.1 Introduction

In the previous chapter, it was discussed that transportation hubs are among the most infection-prone locations during a pandemic. Therefore, it is essential to implement control policies and interventions at transportation facilities to decrease disease transmission. Prior to adopting any control or intervention policies, their efficacy should be evaluated and measured. Therefore, developing appropriate models to assess the effectiveness of control policies and interventions is a critical step in controlling an epidemic. In this section, an epidemic model is developed. First, the fundamentals and assumptions of the developed model are discussed. Then, the proposed model and its components are discussed in detail. Next, an optimization formulation, based on the developed epidemic model is proposed to identify the optimal configuration of a CAV system to help mitigate pandemics.

3.2 A Proposed Methodology for Modeling Epidemic Transmission considering Transportation Impacts

3.2.1. Preliminaries

In this section, the developed epidemiology model and its fundamentals are introduced and discussed. First, we divide the urban trip network into Z trip zones ($i \in Z$). Each trip zone i has a number of travelers $N_{\vec{ij}}^{m}$ that travel from origin i to destination j by travel mode m. To make a trip between any origin-destination (O-D) pair M modes are available. It is assumed that a group of residents of zone i ($\overline{N}_i$) do not travel outside their zone and stay in their zone to carry out their activities there. Therefore, the residents of each trip zone are divided into two main groups: travelers ($N_{\vec{ij}}^{m}$) and non-travelers ($\overline{N}_i$) (Figure 3.1).

It is assumed that travelers make round trips and do not change their initial travel modes over time. The total population of a trip zone i is calculated based on equation (1). It is assumed that the total population of each group (travelers and non-travelers) remains constant over the planning period.

$$N_i = \overline{N}_i + \sum_{m=1}^{M} N_{\vec{ij}}^{m}\ , \forall i \tag{1}$$

It is assumed that there exist four main compartments for the disease transmission process: (i) Susceptible, (ii) Infected, (iii) Exposed, and (iv) Recovered. Therefore, the developed model in this study is generally consistent with the SEIR model in the literature. The Susceptible compartment contains individuals who are in good health and do not have any symptoms of the disease. These individuals are not immune and are therefore vulnerable to getting infected by the virus. The Infected compartment contains those who are infected by the disease and therefore are capable of spreading it. Individuals in this compartment are the cause of the disease's propagation throughout the community where they are located. The Exposed compartment contains individuals that are infected but cannot cause disease transmission (because the virus is not strong enough to spread). The Recovered compartment contains individuals who had the infection, were treated, and have recovered. In the model, the susceptible individuals evolve into the Exposed compartment after physical contact with those in the Infected compartment. Also, individuals in the Exposed compartment become infected after a short time. Individuals in the Infected compartment receive treatment and evolve into the Recovered compartment. Individuals in the Recovered compartment become susceptible again after their period of immunity expires. Figure 3.2 illustrates the general relationships among the four disease transmission compartments.

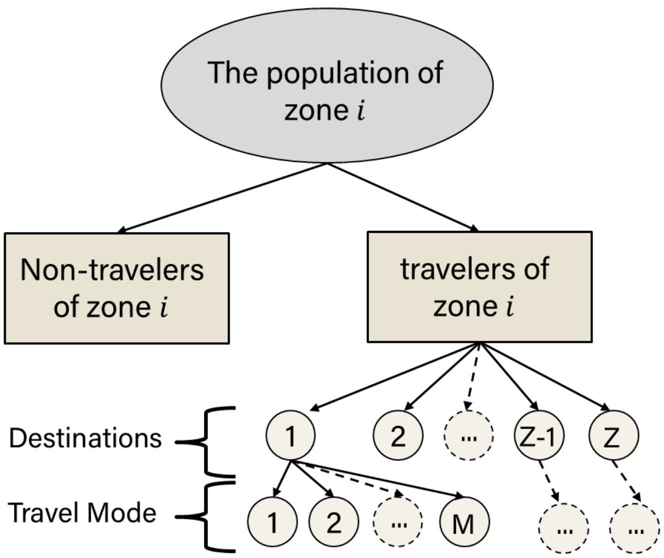


Figure 3.1 The proposed population structure

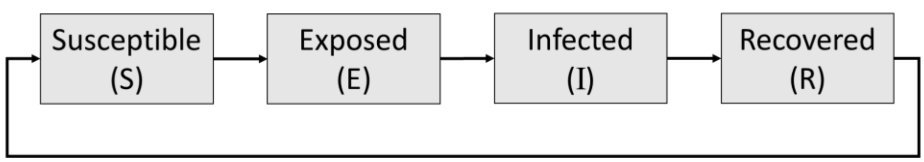


Figure 3.2 Disease transmission compartments

3.2.2. SEIR Epidemic Model

In this study, the locations where the disease transmission process takes place are residential areas, in-vehicle transportation, and activity locations (including workplaces, education centers, and grocery shops). Equations (1)- (15) describe the disease's propagation over the community.

$$\frac{dS_{\vec{ij}}^{m}}{dt} = -\left[f_{1,m}(S,I) + f_{2,m}(S,I) + f_{3,m}(S,I)\right] + \lambda R_{\vec{ij}}^{m} \tag{2}$$

$$\frac{d\bar{S}_i}{dt} = -f_4(S,I) + \lambda \bar{R}_i \tag{3}$$

$$\tilde{S}_i = \sum_{j \in Z} \sum_{m=1}^{M} S_{\vec{ij}}^{m} \tag{4}$$

$$f_{1,m}(S,I) = \alpha_m \left(1 - \theta_{i,j}^{m}\right) S_{\vec{ij}}^{m} \left[\sum_{i\prime, j\prime \in Z} \mu_{m,i' j\prime}^{ij} I_{i' j\prime}^{m}\right] \tag{5}$$

$$f_{2,m}(S,I) = \tilde{\alpha}_i S_{\vec{ij}}^{m} \left[\sum_{i \in Z} \sum_{m=1}^{M} I_{ij}^{m}\right] \tag{6}$$

$$f_{3,m}(S,I) = \bar{\alpha}_i S_{\vec{ij}}^{m} \left[\sum_{j \in Z} \sum_{m=1}^{M} I_{\vec{ij}}^{m} + \bar{I}_i\right] \tag{7}$$

$$f_4(S,I) = \bar{\alpha}_i \bar{S}_i \left[\sum_{j \in Z} \sum_{m=1}^{M} I_{\vec{ij}}^{m} + \bar{I}_i\right] \tag{8}$$

$$\frac{dI_{\vec{ij}}^{m}}{dt} = \beta E_{\vec{ij}}^{m} - \gamma I_{\vec{ij}}^{m} \tag{9}$$

$$\frac{d\bar{I}_i}{dt} = \beta \bar{E}_i - \gamma \bar{I}_i \tag{10}$$

$$\frac{dE_{\vec{ij}}^{m}}{dt} = f_{1,m}(S,I) + f_{2,m}(S,I) + f_{3,m}(S,I) - \beta E_{\vec{ij}}^{m} \tag{11}$$

$$\frac{d\bar{E}_i}{dt} = f_4(S,I) - \beta \bar{E}_i \tag{12}$$

$$\frac{dR_{\vec{ij}}^{m}}{dt} = \gamma I_{\vec{ij}}^{m} - \lambda R_{\vec{ij}}^{m} \tag{13}$$

$$\frac{d\bar{R}_i}{dt} = \gamma \bar{I}_i - \lambda \bar{R}_i \tag{14}$$

$$S_{\vec{ij}}^{m}, E_{\vec{ij}}^{m}, I_{\vec{ij}}^{m}, R_{\vec{ij}}^{m}, \bar{S}_i, \bar{E}_i, \bar{I}_i, \bar{R}_i \geq 0 \tag{15}$$

Equation (2) represents the changes in the population of susceptible travelers of O-D pair (i, j) that use travel mode m ($S_{\vec{ij}}^{m}$). Due to having contact with infected people in residential areas, transportation modes, or activity places, some of the susceptible persons become exposed to the disease and join the Exposed compartment ($E_{\vec{ij}}^{m}$). The disease transmission for susceptible travelers is captured by three main functions ($f_{1,m}$, $f_{2,m}$, and $f_{3,m}$). Moreover, recovered travelers ($R_{\vec{ij}}^{m}$) become susceptible again after an immune period $\frac{1}{\lambda}$. λ represents the average rate at which a recovered person becomes susceptible again. Equation (3) represents the change in the population of susceptible non-travelers of zone i. Similar to equation (2), there is an infection mechanism (presented as f_4) that reduces the population of $\bar{S}_i$ and a population increasing process as recovered group ($\bar{R}_i$) turn into the Susceptible compartment over time. Equation (4) calculates the total travelers of zone i.

Equation (5) describes the infection process for susceptible travelers ($S_{\bar{i}\bar{j}}^{m}$) in travel mode m. This process depends on the infection probability in travel mode m (α_m), percentage of the travelers that use the alternative CAV mode ($\theta_{i,j}^{m}$), the population of $S_{\bar{i}\bar{j}}^{m}$, the total number of infected travelers, between any O-D pairs, that use mode m ($I_{i'j'}^{m}$), and the overlap of trips of O-D pairs (i', j') and (i, j) ($\mu_{m,i'j'}^{ij}$). If their trips overlap $\mu_{m,i'j'}^{ij}$ is 1, otherwise it is 0. Next, the infection process for $S_{\bar{i}\bar{j}}^{m}$ at activity zone (j) is presented in equation (6). This process depends on the population of $S_{\bar{i}\bar{j}}^{m}$, infection probability of ($\tilde{\alpha}_i$), and the total number of infected individuals present at zone (j). Equations (7) and (8) describe the infection process at residential locations, which depends on the infection probability ($\bar{\alpha}_i$), susceptible individuals ($S_{\bar{i}\bar{j}}^{m}$ or $\bar{S}_i$), and total number of infected individuals ($\left[\sum_{j\in Z}\sum_{m=1}^{M} I_{\bar{i}\bar{j}}^{m} + \bar{I}_i\right]$). Next, equations (9) and (10) show the changes in the population of infected travelers and non-travelers, respectively. Equations (11)-(14) represent the changes in Exposed and Recovered compartments. Equation (15) presents the domains of the variables.

3.2.3. Optimal Configuration of CAV System

As mentioned in the previous chapter, transportation modes can significantly influence the rate of disease spread. Therefore, reducing the disease transmission probability in the existing transportation modes or introducing new transportation modes with minimal transmission probability can reduce disease propagation associated with existing transportation systems. Consistent with this study's stated objective, we focus on the latter only.

Recalling the disease propagation mechanism (equations (1)-(15)), $\theta_{i,j}^{m}$ represents the percentage of travelers of O-D pair (i, j) and mode m that switch their modes to the "clean" alternative modes, that is, CAVs. It can also be interpreted as the provided new transportation mode capacity to accommodate the passengers of mode m that travel between O-D pair (i, j). Therefore, it the decision variable in the proposed model. In a pandemic, providing adequate clean CAV modes to serve travelers yields the best outcome in terms of reducing disease transmission in transportation modes (as there is an assumed zero transmission probability associated with these modes).

However, there are some practical constraints, such as the budget or availability of CAVs, that may preclude the deployment of the needed number of CAVs to serve the demand. Moreover, attracting passengers to the new modes can be challenging. Due to the differences in service schedules, service routes, and fares of the new modes, it may be the case that not all passengers are willing to switch to them. Therefore, it is important that transportation planners choose $\theta_{i,j}^{m}$ in a way that addresses the practical challenges. To do this, an optimization program is developed in this study (equations (1)- (19)).

The optimization problem seeks to minimize the total number of persons infected over the planning horizon. A key assumption is that the transportation agency has knowledge of the prospective demand for the new clean mobility during the pandemic. Travelers who shift patronage from their pre-pandemic mode to the new transportation mode during the pandemic, are estimated, and their prospective travel demand can be represented as the modal shift ratio per each O-D pair (i, j) from existing travel mode m to the new travel mode m'. This ratio is presented by $\rho_{i,j}^{m,m'}$. There is total M' potential CAV-based modes. Also, it is assumed that the transportation agency (through policy or collaboration with the private sector) has established the required capacity (i.e., fleet size, service frequency, etc.) of each new mode needed to serve the prospective travel demand. Thus, the decision variable of the optimization problem is defined as the percentage of the required capacity that should be implemented for a CAV-based mode m' ($x_{m'}$). The optimization program is formulated as follows:

$$x_{m'}^{*} = \arg\min_{x_{m'}} \sum_{t \in T} I_t \tag{16}$$

Subject to:

$$\theta_{i,j}^{m} = \sum_{m' \in M'} x_{m'} \rho_{i,j}^{m,m'} \tag{17}$$

$$\sum_{m' \in M'} c_{m'} x_{m'} \leq B \tag{18}$$

$$0 \leq x_{m'} \leq 1 \tag{19}$$

And equations (1)- (15).

Equation (16) minimizes the total number of infected people over the study period by choosing optimal values for $x_{m'}$. Equation (17) shows the relation of $x_{m'}$ and $\theta_{i,j}^{m}$. Equation (18) represents the budget constraint of the problem. In this equation, $c_{m'}$ represents the cost of CAV-based mode m' with its total required capacity and B represents the total budget. Equation (19) shows the domain of the decision variable $x_{m'}$. Also, the optimization problem must satisfy the dynamics of disease propagation over time (equations (1)- (15)).

CHAPTER 4: SAFE MOBILITY BY CAVS IN A PANDEMIC

4.1 Structure and Operation of CAVs During a Pandemic

4.1.1 Introduction

According to Morens et al. (2009), pandemics can be defined as "diseases that extend over large geographic areas, spread via transmission, have high attack rates, spread explosively, are novel, infectious, contagious and severe". All pandemics invariably exhibit these epidemiologic features, with widespread geographic extension being common for all of them. Throughout history, humanity has experienced several pandemics, with the latest one being the COVID-19 pandemic which is caused by the SARS-CoV-2 respiratory virus. Various virus types exhibit different transmission routes for infectious agents. Respiratory viruses such as SARS-CoV-2 spread through four primary modes of transmission: direct contact, indirect contact through contaminated surfaces (fomites), large respiratory droplets, and fine aerosols (Leung, 2021). In this context, Connected and Autonomous Vehicles (CAVs) can prove to be advantageous compared to traditional human-driven vehicles due to their automation and hence lack of a human driver. Some of the key ways where CAVs could help mitigate pandemics are discussed in this chapter.

4.1.2 The Design Perspective

The absence of human drivers in Connected and Autonomous Vehicles (CAVs) is a key advantage over traditional human-driven vehicles, particularly during a pandemic, as it reduces human contact. In this regard, the efficacy of a CAV in mitigating disease spread could be enhanced by further modifying their design equipping them with additional features. Some proposed ideas are presented below.

<u>Ensuring proper airflow and ventilation:</u>

The primary mode of person-to-person spread of SARS-CoV-2 is through respiratory droplets and aerosols (WHO, 2021). When an infected individual coughs, sneezes, talks, or sings, they release respiratory droplets of various sizes into the air. Larger droplets usually travel short distances, around six feet, before falling to the surface. However, what makes SARS-CoV-2 particularly concerning is its presence in aerosol form or minuscule droplets, (measuring less than five microns in diameter) that can stay suspended in the air for extended periods, up to three hours, creating a higher risk of exposure for individuals who are in close proximity to an infected person (van Doremalen et al., 2020). Hence, proper airflow and ventilation are critical for reducing virus transmission.

Simulations conducted by Shu et al. (2022) focus on different scenarios for cleaning the air within a car. They investigated the percentage of remaining marker particles resulting from coughing by a person in various positions within the car. For a car moving at 34 mph with the passenger seated in the front right seat, the optimal ventilation configuration is: open the front right and rear left windows (Figure 4.1). The researchers stated that in this configuration, only 3.31% of marker particles remained inside the car after 10 seconds.

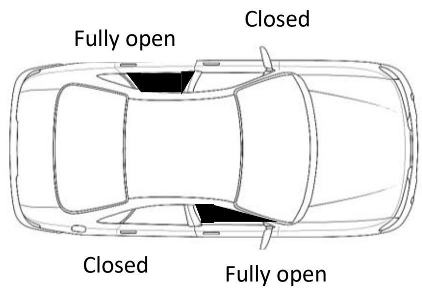


Figure 4.1 Shu et al. (2022)'s recommended window open-close arrangement

The Shu et al. (2022) study also found that in the rear section of the vehicle, it is more difficult to address contamination compared to the front section, because particles released in the rear section are less likely to enter the front-to-back flow field of air that is generated when the windows are opened. Consequently, it is generally safer to sit in the front of the car compared to the rear, a sole passenger boarding the vehicle could be instructed to use the front seat.

Further investigations at different speeds helped identify the most favorable positions for passengers and the ideal window opening configurations. By implementing automated window opening systems that respond to the vehicle's speed and passenger positions, we can create a dynamic and efficient ventilation process. This approach would help disperse potentially contaminated air and replace it with fresh outdoor air, minimizing the concentration of infectious particles inside the car, and thus reducing virus transmission.

Air Filters and UV Lights:

To enhance safety and considering the scenarios where it might not be possible to open windows, equipping CAVs with Ultra-Low Particulate Air (ULPA) and High-Efficiency Particulate Air (HEPA) filters can be beneficial. HEPA and ULPA filters capture 99.97% and 99.99% of aerosols of particle diameter at least 0.3μm and 0.12μm, respectively (Joppolo and Romano, 2017). The choice of appropriate filtration system inside the vehicle can be made based on the pandemic severity and the vehicle's intended purpose.

Furthermore, applying UV-C (Ultraviolet-C) light treatment to the vehicle interior surfaces after each trip could help inactivate the virus and reduce risks of transmission. Studies suggest that a 5-minute UV-C dose of 3.7 mJ/cm^2 to 10.6 mJ/cm^2 is adequate to inactivate the SARS-CoV-2 virus (Choi et al., 2021). Raeiszadeh and Adeli (2020) extrapolated that a UV dose exceeding 20 mJ/cm^2 may likely achieve a 99.9% reduction in virus activity. As there exist potential side effects of UV rays, such UV air treatments could be applied only after each trip, after the passenger has exited the vehicle.

Installation of thermal cameras:

Fever is recognized as a key marker of COVID-19, with any individual having a body temperature exceeding 37.5^o C being regarded as a potential "suspect" for the disease. To address this issue, (Septama et al., 2021) have developed a thermal camera capable of detecting high temperature object within 30 cm to 100 cm. Subsequent to image capture, the camera sends the data to a controller that processes the image and calculates the body temperature of the target object. By installing such thermal cameras in the vehicle, passenger temperatures could be measured instantaneously, and any individuals with high temperatures can be alerted. This approach provides two key advantages: First, passengers can be made aware of their high body temperature and their potential carriership of the virus. Secondly, vehicles can assist in keeping track of potentially sick individuals, contributing to public health efforts in containing the spread of COVID-19.

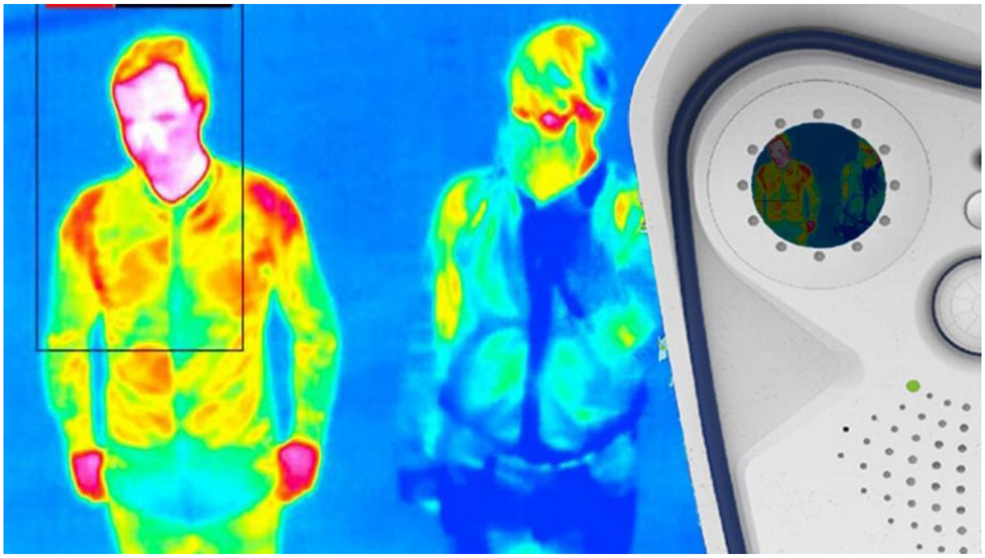


Figure 4.2 Thermal images could be taken of prospective CAV users using the CAV's thermographic sensors
(Source: https://www.mobotix.com/en/products/thermographic-cameras)

<u>Installation of a microphone and a screen for instantaneous COVID-19 tests:</u>
Numerous methods have been developed to detect COVID-19 in individuals, and one of the most convenient methods is the analysis of speech patterns, breathing patterns, and induced cough patterns. The virus affects human glottis, causing restriction or obstruction of the airway, and changing the vocal audio via coughing, breathing, and speech. Analyzing these changes in respiratory sounds could help in the identification of COVID-19 infection in individuals (Pahar et al., 2022).

To conduct this test, the installation of a microphone and a screen is sufficient (Pahar et al., 2022). The test can be completed within a few minutes of boarding the vehicle. The installation of a screen is suggested so that the instructions for the test can be clearly displayed on the screen. Instructions can be in the following forms or any combination thereof:

- Take short breaths five times.
- Take deep breaths five times.
- Say the alphabet.
- Counting
- Cough five times (induced)

Including examples of what kind of sounds are expected for the test can assist passengers in providing accurate data for the algorithm's optimal functioning. To achieve this, a microphone and a screen can be installed in the vehicle, allowing passengers to perform the test as soon as they board. The microphone records the speech, breathing, and cough patterns of the passenger, which can then be analyzed using deep learning techniques to determine if they are infected with COVID-19. Rahman et al. (2022) has developed a stacking Convolutional Neural Network (CNN) with a logistic regression classifier that achieved a detection accuracy of 98.85% and 96.5% for asymptomatic and symptomatic patients, respectively, using cough sound spectrogram images. The detection accuracy for breath sound spectrogram images was found to be 80.01% and 91.03% for asymptomatic and symptomatic patients, respectively.

Lella and PJA (2021) adopted a Data De-noising Auto Encoder to extract the in-depth features of acoustic signals using recorded sounds, followed by using a 1D CNN classifier to make the classification. Their algorithm achieved an accuracy of 90%. The testing process is convenient and can be done in the vehicle itself without the need for external assistance. In case multiple passengers are boarding, they could each take the test. It is also essential to install an automatic mechanism for wiping and sanitizing the screen and the microphone after each test to minimize the risk of virus transmission to future passengers.

Minimalistic interior:

Comfort is a key factor for vehicles used in daily life. Yet still, ensuring safe transportation with a low risk of disease transmission takes precedence during pandemics. As such, it is recommended that Connected and Autonomous Vehicles (CAVs) adopt a minimalistic interior design, with a focus on materials that facilitate easy cleaning and sanitization rather than prioritizing comfort and aesthetic appeal. As per the findings of van Doremalen et al. (2020), the SARS-CoV-2 virus demonstrated varying stability at different surfaces: copper–4 hrs; stainless steel–48 hrs; cardboard–24 hrs, and plastic–72 hrs. Similar tests could be conducted on other materials and the materials for which the virus shows least stability, could be identified for use in the interior design of CAVs intended for use during pandemics.

Behzadinasab et al. (2020) found that stainless steel and glass coated with cuprous oxide and polyurethane demonstrate the ability to deactivate the virus by up to 99.9% within just one hour. Moreover, the coating exhibited excellent durability during crosshatch testing and remained intact and active even after being immersed in water for 13 days. Such coatings may be used in the door handles, seats, buttons, etc. inside the vehicle. Additionally, CAVs could be designed with contactless entry and exit mechanisms such as voice commands, or gestures, eliminating the need for physical contact with surfaces that could be contaminated.

Installation of sanitizer sprays:

Among the various methods available for neutralizing the SARS-CoV-2 virus, washing with soap and water, and using sanitizers or disinfectants are the most popular due to ease and affordability. Cleaning the vehicle thoroughly with soap and water may be done at frequent intervals, but this process can be time-consuming and require a significant amount of energy. Therefore, using sanitizers may be a more feasible option. To ensure optimal sanitization, sanitizer sprays can be strategically placed inside CAVs, enabling the sanitizer liquid to reach most exposed surfaces to eliminate any virus present on them. In addition, adopting a minimalistic interior design can facilitate the sanitization process by reducing the number of surfaces that need to be cleaned.

As demonstrated by (Jadhav et al., 2021), using six nozzles to spray sanitizer at 360 degrees can reach all the nooks and corners of a bus to achieve proper sanitization, which could be accomplished within five minutes. Using this approach, similar results can be expected for a CAV as well. Moreover, to enhance convenience, sanitizers could be sprayed in the form of frost to ensure that the seats do not remain wet after spraying (Jadhav et al., 2021).

4.1.3 The Operations Perspective

In addition to appropriately designing CAVs and embedding them with the necessary equipment, proper planning from the operational perspective would help utilize them much more efficiently. To fully optimize the utilization of CAVs, it is important to consider operational planning in addition to design and equipment considerations. Only then could CAVs be used to their full potential in providing safe, efficient, and sustainable transportation for individuals and communities. A few ideas (from the operations perspective) are listed below.

Division of shared-use vehicles into two separate fleets:

It is recommended to classify CAVs into two fleets based on their purpose and potential for virus transmission in order to minimize the spread of COVID-19. The first fleet should consist of vehicles used for transporting infected individuals, medical personnel attending to COVID-19 patients, delivering supplies to quarantine zones, etc. These vehicles should be thoroughly cleaned and sanitized after each trip to minimize the risk of transmission.

The second fleet may contain CAVs used for normal transportation purposes, such as delivering goods and transporting healthy individuals. Sanitization and cleaning should still be performed but may be done less frequently than in the first fleet. The number of vehicles in each fleet can be determined by the rate of virus spread, the number of infected individuals, etc. Implementing this approach could significantly reduce contact between infected and healthy individuals, ultimately decreasing virus transmission.

Mask compulsion rules:

There is no question that masks are effective in reducing COVID-19 transmission (Brooks and Butler, 2021). It has been reported that at least 50% or more of virus transmissions occur from infected individuals who are still in the pre-symptomatic phase (Johansson et al., 2021). As such, mandating the use of masks for all passengers of CAVs could play a significant role in reducing the virus transmission. This policy could also promote the adoption of mask-wearing as a social norm, encouraging individuals to continue wearing masks even after they have left the vehicle. By implementing this policy, the health safety of CAVs and the effectiveness in mitigating COVID-19, could be enhanced.

In addition to reducing contact between infected and non-infected individuals, CAVs offer numerous other advantages. They enable efficient tracking of the movements of infected and potentially infected people, which can greatly aid in contact tracing efforts. By maintaining a collective record of passengers' movements, contact tracing becomes more streamlined and convenient. In critical situations, collaboration with mobile phone carriers and agencies with access to CCTV footage can enable extensive contact tracing capabilities. These advanced features of CAVs make them incredibly valuable in pandemic situations, thereby facilitating proactive response to outbreaks and protecting public health.

General operational rules and design:

Figure 4.3 presents a graphic of proposed ride-sharing shuttle interiors planned by Cruise for the COVID-19 era. The operational rules include minimize talking to each other or on phone, and the design features include more windows, larger windows, windows on all sides including the rear and roof of the vehicle, optimal opening-closing configuration of windows to facilitate exit of air in the cabin, autonomous windows, and passenger distancing seat arrangements (Automotive News, 2020).

Figure 4.3 The interior of a ride-sharing shuttle for the COVID-19 era
(Automotive News, 2020)
(Source: www.autonews.com/design/cruise-adapts-planned-ride-sharing-shuttles-covid-era)

4.2 Analyzing the Benefits of CAV in Mitigating a Pandemic

In this section, different numerical analyses are conducted using the developed epidemic model and optimization formulation. To do this, a synthetic transportation network is developed. The developed network has six zones (Figure 4.4). Four of the zones are residential areas that generate trips, and two of the zones are activity zones that attract trips. In this network, there are three transportation modes that differ in trip demand and disease transmission probabilities.

The details of these modes are as follows: (i) Mode 1 (trip share: 60%, relative infection risk: high), (ii) Mode 2 (trip share: 20%, relative infection risk: Medium), and (iii) Mode 1 (trip share: 20%, relative infection risk: low). The introduced modes can be interpreted as follows: Mode 1 represents mass transit (such as heavy rail and bus rapid transit) modes that have the highest passengers and therefore the highest infection level relative to the other modes; Mode 2 represents lighter transit modes (such as buses or light rail transit (LRT)) that have lower passenger and infection rates compared to mass transit modes; and last, Mode 3 represents other transportation modes that have a lower infection risk relative to the other modes, such as ride-share, shuttles, and ride-hailing.

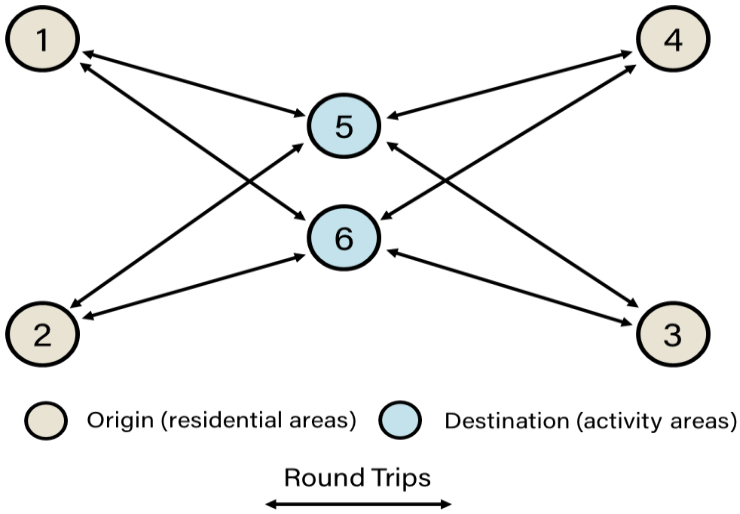


Figure 4.4 Synthetic network

Two sets of experiments are conducted. In the first set, the effects of CAVs on mitigating a pandemic are analyzed under conservative and non-conservative behavior of people, and in the second set, the sensitivity of the mitigation effects of CAVs to their deployed capacity and the available budget, are analyzed. Moreover, the COVID-19 pandemic and a 2-year period are considered the case study and study horizon of the numerical experiments.

4.2.1 Effects of CAVs on Pandemic Spread

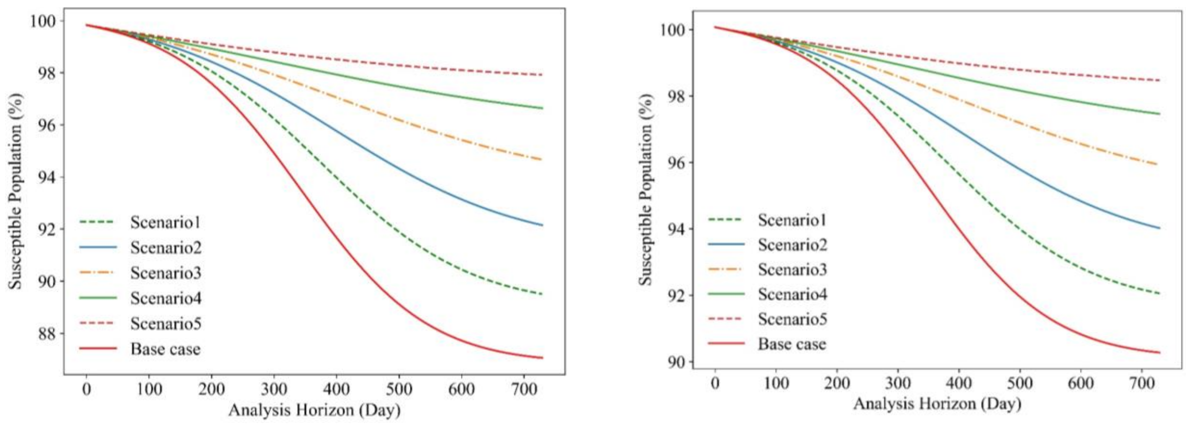
Three CAV-based systems are proposed to work in the transportation network to decrease the pandemic's impacts. Each of these CAV-based systems is considered an alternative to the existing modes (Modes 1, 2, and 3). Based on the capacity of the proposed CAV-based system, different scenarios are developed where the CAV-based system can serve different portions of travelers. In this regard, scenarios 1-5 serve 20%, 40%, 60%, 80%, and 100% of the travelers, respectively. As mentioned before, it is assumed that in Recovered compartment, individuals (both travelers and non-travelers) become susceptible to the disease again after their period of immunity expires. In this regard, it is assumed that an individual in the Recovered compartment after recovery may exhibit any one of two behaviors: (a) they adopt a conservative social behavior to prevent becoming infected again; or (b) they revert to their pre-infection social behavior with minimal or no caution. According to these two behaviors, two experimental cases are defined under which the efficacy of the CAV-based system is studied.

<u>Case 1: With Conservative Behavior</u>

In this sub-section, the propagation of the pandemic under conservative behavior is analyzed. In this regard, the evolutions across the compartments (Susceptible, Exposed, Infected, and Recovered) in each group (travelers and non-travelers) are depicted in Figure 4.5. The presented population percentages are calculated based on the population of each compartment relative to the overall population in the Travelers and Non-travelers' groups. Therefore, the sum of the compartment populations in each group (Travelers vs. Non-travelers) is 100% at any time stamp. In all the scenarios, the population of the Susceptible compartments decreases gradually. This is because of the evolution of individuals from the Susceptible compartments to other compartments (Exposed, Infected, and Recovered) over time. Moreover, the population and the rate of conversion of the Susceptible compartment to Exposed compartment are higher compared to those of Recovered compartment. Therefore, regarding the Susceptible compartment, the outflow population exceeds the inflow population, leading to a progressive decrease in the population of individuals in that compartment.

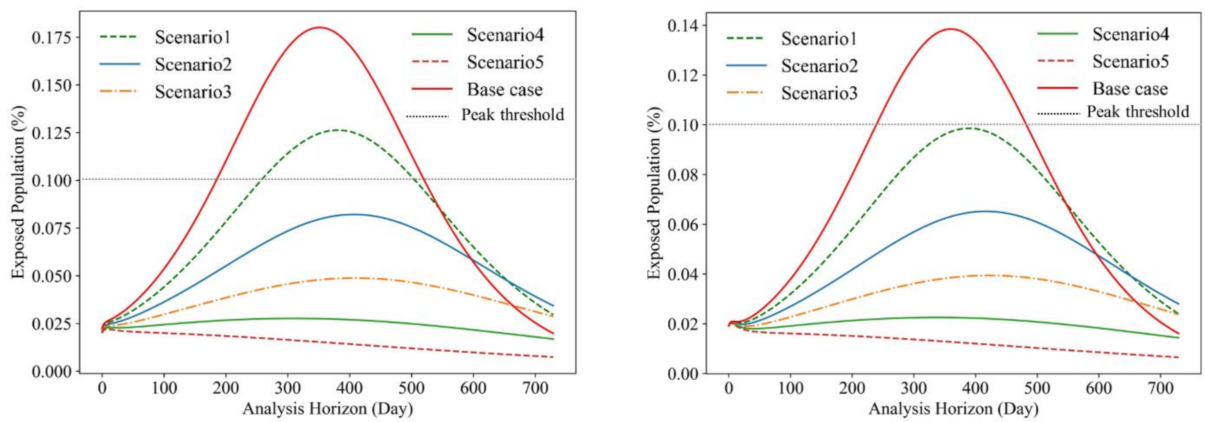
It is observed that at the end of the analysis period, the Susceptible compartment has the lowest population under the base case. Also, the Susceptible population increases as the capacity (or fleet size) of clean CAV modes increases. It can be noted that a higher population of the Susceptible compartment does not necessarily mean that the community has a higher proportion of disease-vulnerable individuals; rather, it means that there is a higher proportion of uninfected and unexposed individuals in the community. This, clearly, is a positive outcome of introducing the CAV fleet to the transportation system in the community. In other words, the CAV fleet can significantly change the dynamics of the disease propagation toward more beneficial outcomes. This positive effect can be observed further in Figure 4.5 (b) and (c), where the changes in the distribution of the Exposed and Infected compartment sizes are presented.

Overall, in scenarios 1-5 of the analysis, the relative population of the Exposed and Infected compartments are lower compared to the base scenario. Moreover, increasing the capacity of CAV systems from 20% (Scenario 1) to 100% (Scenario 5) causes a greater reduction in the population of the Exposed and Infected compartments. It is interesting to observe that although the population of Exposed and Infected individuals are higher in the base scenario compared to scenarios 1-5 but are lower compared to the numbers in Scenarios 3-5 during the last 100 days of the analysis period. This is because the lower susceptible population in the base case contributes to fewer exposed and infected persons (Figure 4.5 (a)) and should be interpreted as the superiority of the base case during the last period of the analysis. Lastly, it is observed that the CAV system reduces the recovered population as the numbers of exposed and infected persons reduce (Figure 4.5 (d)). Similar to what was discussed regarding the other compartments, increasing the capacity of the proposed system will significantly reduce the number of people in the Recovered Compartment.



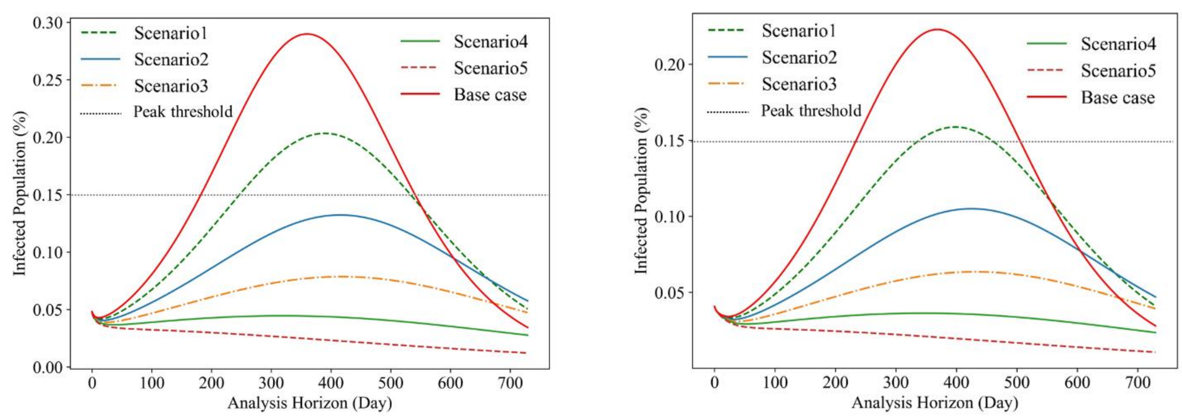
Travelers Non-travelers

(a) Susceptible compartment



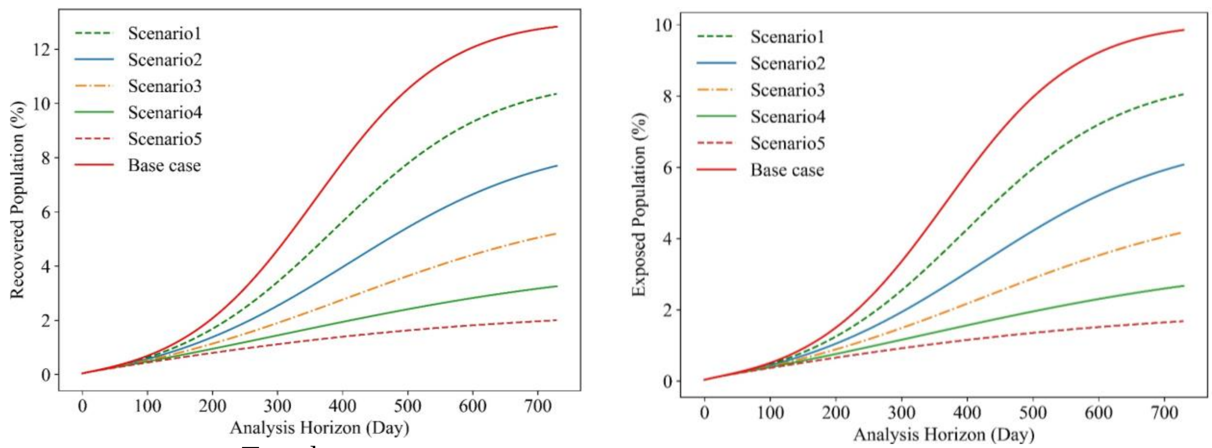
Travelers Non-travelers

(b) Exposed compartment



Travelers Non-travelers

(c) Infected compartment



Travelers Non-travelers

(d) Recovered compartment

Figure 4.5 Evolution of the compartments in Case 1

It can also be observed that, besides the changes in compartment populations, the operation of the CAV system has interesting effects on the severity and duration of the pandemic peak. In this study, the **pandemic peak** is defined based on thresholds for Exposed and Infected compartments. So, if the population of Exposed or Infected compartments exceeds the defined thresholds, the peak starts, and when they revert to below the thresholds, the peak has subsided. In this study, we assume 0.1% and 0.15% thresholds for the Exposed and Infected compartments, respectively. We also consider the **peak duration** as the interval of time between the start and the end of the peak, and the **peak severity** as the total number of exposed and infected people during the peak. The simulation results suggest that the introduction of the proposed CAV system in the transportation network decreases both the severity and duration of the peaks.

From Figure 4.5 (b) and (c), it can be observed that the peak condition appears only in the base case and Scenario1 (which has a 10% CAV system), and the rest of the scenarios that leverage the operation of the proposed CAV system do not experience the peak condition. In this regard, both duration and severity decreased after introducing 10% of CAV systems. In Figure 4.5 (b) and (c), the severities of two scenarios can be compared by examining the corresponding area bounded by the curve (the area between the curve and the threshold line).

Table 4.1 presents the average populations of compartments over the 2-year period. In this regard, introducing the proposed CAV system and increasing its capacity have significant positive effects in terms of disease propagation reduction. For example, in the base-case scenario, 0.10% and 0.16% of travelers are exposed and infected, respectively. However, after introducing the proposed CAV system (Scenario5), only 0.01% and 0.02% of travelers become exposed and infected, respectively. This is similar to the patterns presented in Figure 4.5.

Table 4.1 Average populations of compartments (%)

Case1

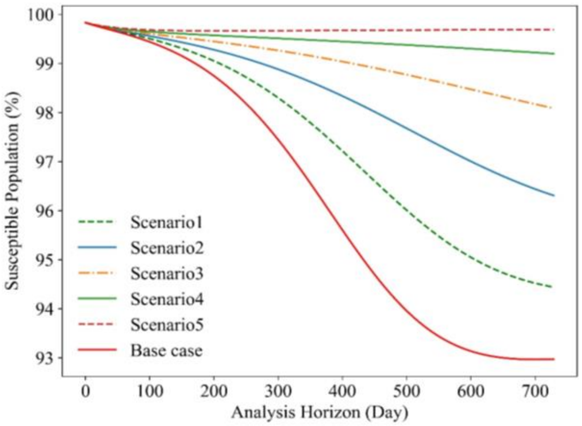
	Travelers					**Non-travelers**				
	S	E	I	R	Total	S	E	I	R	Total
Base-case	93.22	0.10	0.16	6.46	100	95.10	0.07	0.12	4.88	100
Scenario1	94.80	0.08	0.13	4.93	100	96.24	0.06	0.10	3.77	100
Scenario2	96.22	0.06	0.09	3.57	100	97.27	0.05	0.07	2.78	100
Scenario3	97.36	0.04	0.06	2.48	100	98.12	0.03	0.05	1.97	100
Scenario4	98.17	0.02	0.04	1.70	100	98.74	0.02	0.03	1.38	100
Scenario5	98.71	0.01	0.02	1.19	100	99.15	0.01	0.02	0.99	100

Case2

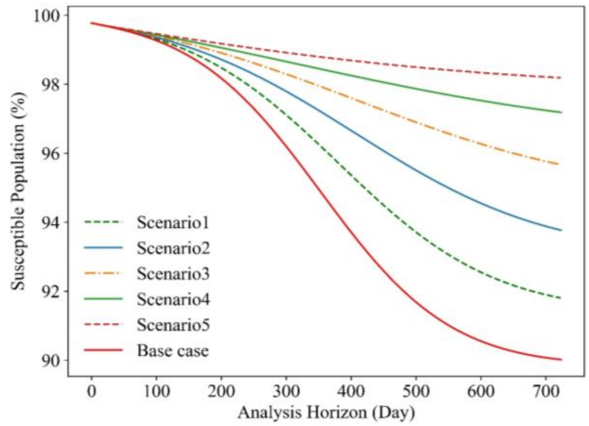
	Travelers					**Non-travelers**				
	S	E	I	R	Total	S	E	I	R	Total
Base-case	96.31	0.29	0.46	2.88	100	97.44	0.22	0.35	2.16	100
Scenario1	97.40	0.21	0.33	2.01	100	98.23	0.16	0.25	1.53	100
Scenario2	98.36	0.13	0.21	1.24	100	98.94	0.10	0.16	0.97	100
Scenario3	99.06	0.07	0.11	0.69	100	99.47	0.06	0.09	0.55	100
Scenario4	99.47	0.04	0.06	0.37	100	99.79	0.03	0.05	0.30	100
Scenario5	99.68	0.02	0.03	0.21	100	99.96	0.02	0.03	0.17	100

Case 2: Without Conservative Behavior

For the second case of the experiments, we assume that the individuals in the Recovered compartment become susceptible again shortly after they recover (50-day expiry of immunity). Similar to the analyses in Case 1, the population of compartments over a 2-year period is analyzed. Figure 4.6 shows the population of each compartment in Case 2 over time. Compared to the populations of compartments in Case 1 (Figure 4.5), the populations of Exposed and Infected compartments are much higher in Case 2 each day. On average, the populations of Exposed and Infected compartments corresponding to each scenario of Case 2 are higher compared to those of the corresponding scenarios of Case 1 (Table 4.1). Moreover, in the experiments of Case 2, the pandemic does not reach a peak but stays steady for the rest of the analysis period. This highlights the importance of individuals adopting preventive and control actions during a pandemic. Moreover, similar to what is discussed in the experiments of Case 1, introducing the proposed CAV systems and increasing their capacities leads to a decrease in the exposed and infected populations and an increase in the susceptible and recovered populations. This result suggests that it is feasible to use the proposed CAV system to help in on pandemic control and mitigation.

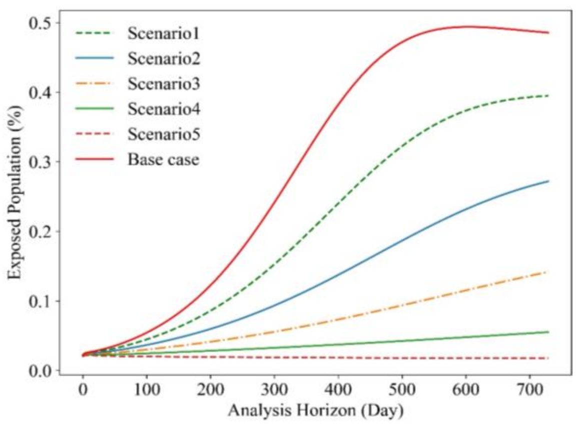


Travelers

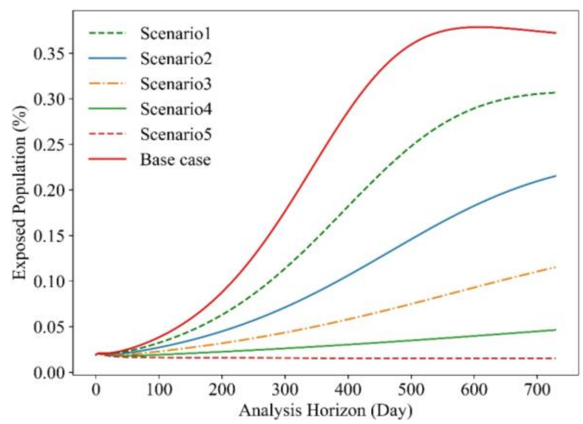


Non-travelers

(a) Susceptible compartment

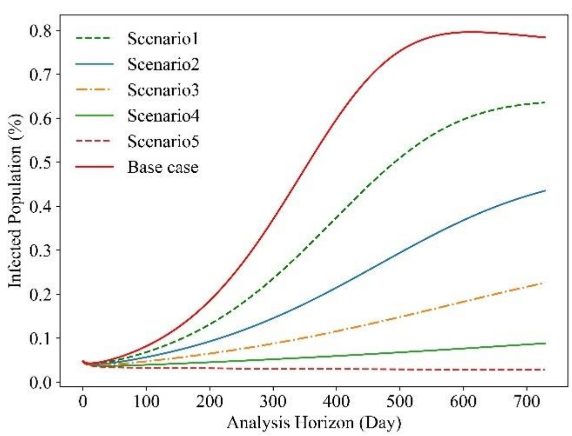


Travelers

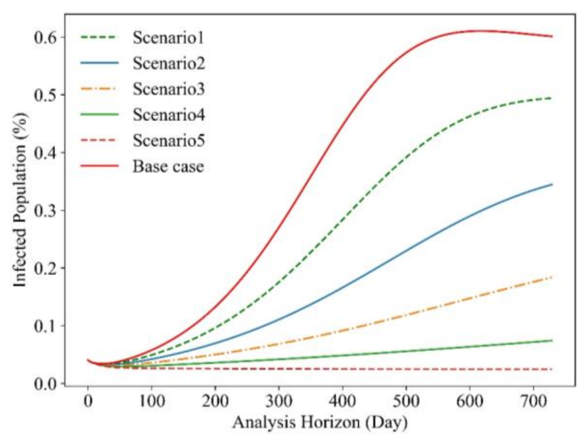


Non-travelers

(b) Exposed compartment

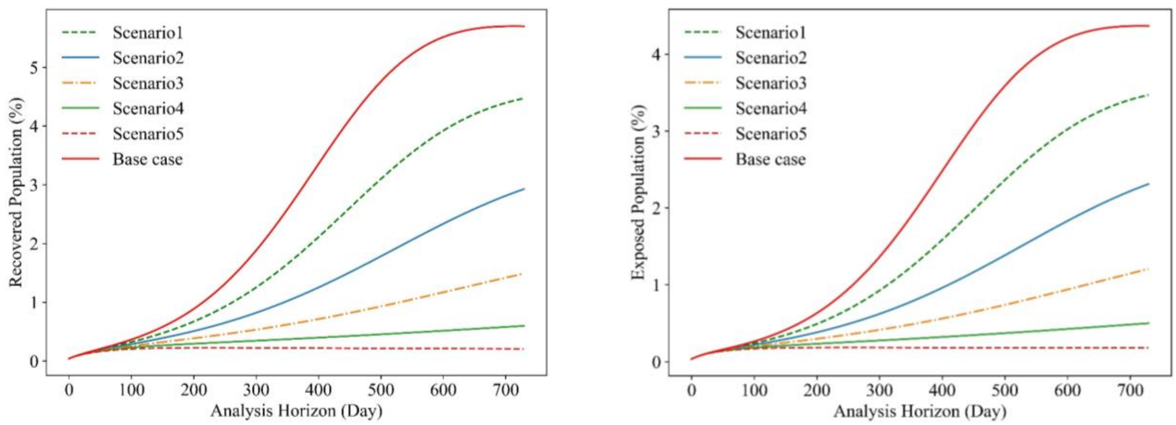


Travelers



Non-travelers

(c) Infected compartment



Travelers Non-travelers

(d) Recovered compartment

Figure 4.6 Evolution of the compartments in Case 2

4.2.2 Budget Sensitivity Analysis

In the previous sub-section, we discussed the efficacy of CAV systems in pandemic control. We showed that CAV systems could be considered an effective way to decrease the spread of pandemics in a community by decreasing the exposed and infected population. However, deploying the proposed CAV system or upgrading the existing transportation systems to include a CAV system such as the one proposed, is costly. The transportation agency may only provide an optimal and effective CAV-system deployment plan that meets its budget and other constraints. Therefore, practical constraints, such as budget, play an important role in forming the CAV system.

In this sub-section, we analyze the relationship between budget level and optimal configuration of the proposed CAV system and its corresponding effects on the pandemic by solving equations (1)-(19). In this set of numerical experiments, we assume an exclusive alternative CAV-based system for each of the existing transportation systems. These CAV systems are different in terms of capacity and, therefore, investment and operation costs. In this regard, we assume the required budget to accommodate 100% of travelers in each existing mode is as follows: Mode 1: 60, Mode 2: 30, and Mode 3: 20 monetary units. Moreover, the required budget to accommodate any portion of travelers (or, in other words, the capacity) is proportional to the required budget at 100% level. For example, the required budget to deploy CAV systems to accommodate 40% of travelers in Mode 1 is 24 monetary units. Also, based on the assumed required budget, 110 monetary units are required to deploy CAV systems to accommodate all of the travelers. So, in this case, all the transportation modes are CAV, and no one uses conventional modes such as HDV.

To investigate the effects of budget on CAV system configuration and its corresponding effects on the pandemic, we solve the presented optimization problem (equations (2)-(19)) under different budget levels. The budget levels range from 0 (which means no CAV system deployment) to 110 (which is enough budget to accommodate all of the travelers with CAV systems). Figure 4.7 shows both the optimal solutions and the corresponding average (over the 2-year study horizon) of the Exposed and Infected compartments. In this figure, the solid blue curve shows the average infected population (the percentage of the whole community) corresponding to each level of budget. Also, Figure 4.6 shows the optimal solution (or configuration of CAV systems) based on different budget levels. The numerical results show that deploying CAV systems for the travelers of Mode 1 is the optimal solution from budget 0 to 60 (the orange area of Figure 4.7).

Also, the capacity of the CAV system (from 0 to 100%) corresponding to any budget in that area is shown on the horizontal axis at the top of the chart. For example, the optimal solution for budget level 30 is CAV systems with a capacity to accommodate 50% of travelers in Mode 1. The reason for deploying CAV systems only for travelers in Mode 1 is that Mode 1 has the highest infection risk. Therefore, providing CAV alternatives for Mode 1 has higher effects than other modes on decreasing the number of infected people. For the same reason, for any budget from 60 to 90, CAVs for travelers in Mode 1, with 100% capacity, and Mode 2 are deployed in the network. For instance, if the available budget is 70 units, the optimal solution is to serve 100% of Mode 1's travelers and about 34% of Mode 2's travelers.

Finally, if there is adequate budget to deploy CAV systems for the travelers in both Mode 1 and Mode 2, the extra budget is spent on providing CAV systems for Mode 3. For example, if there are 100 units of budget CAV systems, they serve 100% of the travelers in both Mode 1 and Mode 2 and 50% of the travelers in Mode 3.

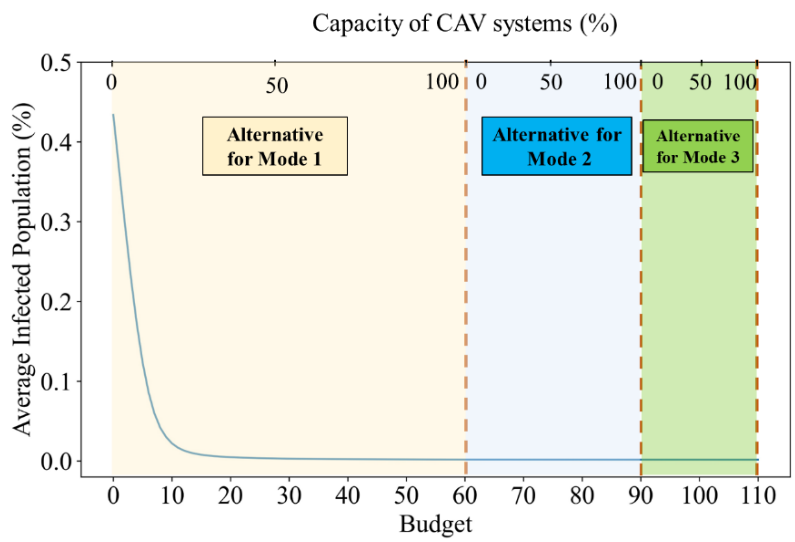


Figure 4.7 Optimal solutions vs. budget level

Figure 4.7 presents the average infected population corresponding to the optimal solution for each budget level. It can be observed that increasing the budget level results in a significantly lower average infection rate due to the deployment of more CAV systems. Interestingly, increasing the budget from 0 to a specific level (about 10 units) causes a large drop in the average infection rate. We refer to this level of budgeting as the "efficient budget." Increasing the budget to any level beyond the efficient budget (10 units) does not decrease the infection rate considerably. Therefore, to reduce the average number of infected people to almost its minimum possible value, it is not worthwhile to convert all the existing transportation systems to the proposed CAV system only during the pandemic. The results suggest that even by serving about 34% of the travelers in Mode 1, which is the mode with highest propensity for infection, the effectiveness of the proposed CAV system in terms of controlling the pandemic is considerable.

CHAPTER 5: CONTROL POLICIES AND INTERVENTIONS DURING PANDEMICS

5.1 Control Policies and Interventions

The introduction of control interventions including policies during a pandemic is crucial to mitigate the spread of the disease, protect public health, and minimize the impact on society. The specific policies and interventions implemented can vary depending on the nature of the pandemic, its severity, and the affected population. In this chapter, we identify a few pandemic mitigation interventions. We do this first for pandemics in general and then for airborne pandemics specifically. Therefore, this chapter serves as an appropriate prelude to the subsequent chapter (Chapter 6) which provides methodologies to assess the effectiveness of pandemic mitigation interventions.

5.1.1 During a pandemic

Below are some common control policies and interventions that may be implemented during a pandemic:

i. **Quarantine and Isolation**: Quarantine involves restricting the movement of persons that have been exposed but are not yet symptomatic, while isolation is for individuals who are confirmed or suspected to be infected. This helps prevent further transmission of the virus (Control et al., 2003; Yan & Zou, 2008; Yan et al., 2007).
ii. **Social Distancing**: Encouraging or mandating people to maintain a physical distance from others, limiting large gatherings, and reducing non-essential travel to minimize close contact and transmission (Aquino et al., 2020).
iii. **Mask Mandates**: Requiring or recommending the use of masks or face coverings in public places, particularly where physical distancing is challenging. Masks help reduce the transmission of respiratory droplets containing the virus (Wright et al., 2020).
iv. **Travel Restrictions**: Implementing restrictions on international or domestic travel, such as border closures, travel bans, or mandatory testing and quarantine measures for travelers (Epstein et al., 2007; Hollingsworth et al., 2006).
v. **Surveillance and Early Detection**: Establishing robust surveillance systems to monitor the spread of disease, track outbreaks can help identify new cases early. Early detection allows for quick containment measures to prevent further transmission (Briand et al., 2011; Ibrahim, 2020).
vi. **Contact Tracing and Testing**: Identifying and notifying individuals who have been in close contact with confirmed cases and encouraging them to get tested. Widespread testing helps in early detection and containment of the virus (Mazza et al., 2021; Pozo-Martin et al., 2023).
vii. **Vaccination Campaigns**: Encouraging vaccination among eligible populations to build immunity and reduce the severity of the disease (Angeli et al., 2022).

viii. **Enhanced Hygiene Measures**: Promoting regular handwashing, using hand sanitizers, and maintaining proper hygiene practices to reduce the risk of transmission (Dalton et al., 2020; Irelli et al., 2020).

ix. **Workplace and School Guidelines**: Implementing safety measures in workplaces and educational institutions, such as staggered shifts, remote work, and hybrid learning models (Ferguson et al., 2006; Qualls et al., 2017).

x. **Public Awareness Campaigns**: Educating the public about the importance of following guidelines and encouraging responsible behavior to control the spread of the virus (Evison et al., 2021).

xi. **Healthcare System Strengthening**: Expanding healthcare facilities, ensuring an adequate supply of medical equipment and medications, and training healthcare workers to handle the increased patient load (Cancedda et al., 2016; Kraef et al., 2020; Peiris et al., 2021).

xii. **Economic Support**: Providing financial assistance and support to individuals and businesses impacted by the pandemic to alleviate economic hardships (Gholipour et al., 2023; Kurdin et al., 2020).

xiii. **Risk Communication and Transparency**: Maintaining open and transparent communication with the public about the status of the pandemic, measures being taken, and any changes in guidelines (Lowe et al., 2022; Menon & Goh, 2005; Zhang et al., 2020).

xiv. **Psychological and Social Support**: Addressing the mental health and social well-being of the population, as pandemics can lead to increased stress, anxiety, and isolation (Chen et al., 2021; Özmete & Pak, 2020; Szkody et al., 2021).

xv. **Data Monitoring and Research**: Collecting and analyzing data to understand the progression of the pandemic, identify high-risk areas, and inform evidence-based decision-making (Bragazzi et al., 2020).

xvi. **Community Engagement**: Involving communities in the response efforts, seeking their feedback, and tailoring interventions to local needs and contexts (Eder et al., 2021; Tambo et al., 2021).

It is important to note that the implementation of these policies and interventions should be based on scientific evidence, risk assessments, and coordination between government authorities, public health agencies, and other relevant stakeholders. The success of these measures largely depends on public cooperation and adherence to the guidelines. Flexibility and adaptability in response strategies are also essential as the situation may evolve rapidly. Additionally, international collaboration and information sharing among countries can help control the global spread of the pandemic and facilitate the development of effective solutions.

5.1.2 During an airborne pandemic

If a pandemic is airborne, it means that the virus causing the pandemic can spread through tiny airborne particles (i.e., aerosols) that remain suspended in the air for an extended period, making transmission easier and potentially affecting a larger number of people. Airborne transmission poses unique challenges for control policies and interventions, as it requires specific measures to limit the spread of the virus effectively. In such cases, the following additional or modified interventions may be implemented:

i. **Improved Ventilation**: Ensuring proper ventilation in indoor spaces, particularly in crowded places like public transportation, healthcare facilities, schools, and workplaces, can help disperse and dilute the concentration of airborne viruses (Persily & Siegel, 2022).
ii. **Air Filtration Systems**: Implementing high-efficiency air filtration systems in enclosed spaces to reduce the presence of viral particles in the air (Blocken et al., 2021; Mousavi et al., 2020).
iii. **N95 or Equivalent Masks**: Recommending or mandating the use of N95 respirators or equivalent masks for individuals in high-risk settings to provide better protection against airborne transmission (Azap & ERDİNÇ, 2020; Gralton & McLaws, 2010).
iv. **Occupancy Limits**: Reducing the occupancy limits in indoor spaces to maintain physical distancing and reduce the risk of viral transmission through the air (Bazant & Bush, 2021).
v. **Outdoor Activities Promotion**: Encouraging outdoor activities and gatherings, where the risk of airborne transmission is lower than in enclosed spaces. Outdoor activities also improve mental health (Jackson et al., 2021).
vi. **Limiting Indoor Gatherings**: Implementing occupancy limits and restrictions on gatherings in enclosed spaces to minimize the risk of airborne transmission (Bazant & Bush, 2021).
vii. **Quarantine Measures for High-Risk Individuals**: Providing additional protections and quarantine measures for vulnerable populations, such as the elderly or those with underlying health conditions (Yan & Zou, 2008).
viii. **Increased Testing and Surveillance**: Implementing widespread testing and surveillance to detect and isolate cases promptly, preventing further airborne transmission (Mazza et al., 2021).
ix. **Public Health Education**: Educating the public about the risks of airborne transmission and the importance of adhering to preventive measures (Anwar et al., 2020; Li et al., 2020).
x. **Rapid Response Teams**: Establishing specialized response teams capable of quickly identifying and containing outbreaks associated with airborne transmission (Loayza-Alarico et al., 2020).
xi. **International Collaboration**: Collaborating with other countries to share information and coordinate efforts in controlling the spread of the airborne virus globally (Fry et al., 2020; Kinsella et al., 2020).

5.2 Discussion

In a pandemic, it becomes even more crucial for individuals and communities to remain vigilant and adhere to preventive measures. Government agencies and public health authorities must work together to evaluate the extent to which their policies and interventions have been effective. The next chapter (Chapter 6) presents the methodologies and metrics for assessing the efficacy of the control policies and interventions that were presented in the current chapter.

CHAPTER 6 MEASURING THE EFFECTIVENESS OF PANDEMIC CONTROL MITIGATION POLICIES INTERVENTIONS

6.1 Introduction

As is the case in any system, it is useful to evaluate the benefits of an intervention retrospectively (in the past) or prospectively (planned) (Labi, 2014). In the context of this report, an "intervention" refers to a pandemic mitigation intervention (PMI) examples of which are presented in the previous chapter of this report. These include CAV-related policies that are described in earlier sections of this report.

This chapter presents a few constructs that indicate the performance of a public health system (SPI) and for assessing the extent to which a PMI has been beneficial – this is referred to as a measure of effectiveness (MOE). Generally, an MOE that is expressed in terms of an appropriate SPI helps (a) assess how far a specific PMI has succeeded (or is anticipated to succeed) in achieving its intended objectives or (b) compare the extents to which alternative PMIs were effective or are going to be effective. In this chapter, first, a few SPIs are identified, and then some MOE constructs are established to help assess PMI effectiveness in terms of the appropriate SPIs.

6.2 PMI Classes and Types

Pandemic mitigation interventions may be categorized in several ways, based on their costs (which may be direct, indirect, or even intangible), benefits, scope, impacts, and so on:

a) the funding source or implementation body – public vs. private sector, or combined (P3)
b) the intended scope: region-wide, city-wide, area-wide, etc.
c) the level of management: strategic vs. operational vs. tactical
d) physical vs. non-physical nature of the PMI
e) the cost to the health agency or the administrative jurisdiction
f) the out-of-pocket cost to individuals of the general public
g) the indirect cost to the public, such as, the loss of income
h) the intangible cost to the public, such as, inconvenience or discomfort

Within these categories, PMIs that have been applied widely to control the COVID-19 pandemic include improved ventilation, air filtration systems, mask mandates (Figure 6.1), occupancy mandates, quarantine measures for high-risk individuals, and rapid response teams (Table 6.1) and other initiatives (Table 6.2). The "mode" of specially designed and managed CAVs proposed in the current study, can be considered a PMI.

The PMIs presented in Table 6.1 (which focuses on airborne transmittable disease such as COVID-19) include improved ventilation, air filtration systems, N95 or equivalent masks, mandates on occupancy limits, quarantining high-risk individuals, and rapid response teams. In Table 6.2 which addresses all transmittable diseases, the PMIs include quarantine and isolation, social distancing, travel restrictions, surveillance and early detection, contact tracing and testing, vaccination campaigns, enhanced hygiene measures, workplace and school schedule changes, public awareness campaigns, healthcare system strengthening, economic support, risk communication and transparency, and psychological and social support.

Table 6.1 PMIs Commonly Applied to Control the COVID-19 Pandemic

PMI	**Details**	**Reference(s)**
Improved Ventilation	Ensuring proper ventilation in indoor spaces, particularly in crowded places like public transportation, healthcare facilities	Persily & Siegel, 2022
Air Filtration Systems	Implementing high-efficiency air filtration systems in enclosed spaces to reduce the presence of viral particles in the air	Blocken et al., 2021; Mousavi et al., 2020
N95 or Equivalent Masks	Recommending/mandating N95 mask use for individuals in high-risk settings to provide better protection against airborne transmission	Azap & ERDİNÇ, 2020; Gralton & McLaws, 2010
Mandates on Occupancy Limits	Reducing the occupancy limits in indoor spaces to maintain physical distancing and reduce the risk of viral transmission through the air	Bazant & Bush, 2021
Quarantining High-risk Individuals	Providing quarantine measures for vulnerable populations, such as the elderly or those with underlying health conditions.	Yan & Zou, 2008
Rapid Response Teams	Establishing specialized response teams capable of quickly identifying and containing outbreaks associated with airborne transmission	Loayza-Alarico et al., 2020

See Table 6.2 for additional list of PMIs.

Figure 6.1 Policies on mask wearing and proper ventilation could represent an effective pandemic mitigation intervention (*source: unsplash.com*)

Table 6.2 PMIs Commonly Applied to Control Pandemics in General

PMI	**Details**	**Reference(s)**
Quarantine and Isolation	Restricting the movement of persons that have been exposed to the virus but are not yet symptomatic, while isolation is for individuals who are confirmed or suspected to be infected. This helps prevent further transmission of the virus.	Control et al., 2003; Yan & Zou, 2008; Yan et al., 2007
Social Distancing	Mandating people to maintain a minimum physical distance from others, limiting large gatherings, and reducing non-essential travel to minimize close contact and transmission.	Aquino et al., 2020
Mask Mandates	Requiring or recommending the use of masks or face coverings in public places, particularly where physical distancing is challenging. Masks help reduce the transmission of respiratory droplets containing the virus.	Wright et al., 2020
Travel Restrictions	Implementing restrictions on international or domestic travel, such as border closures, travel bans, or mandatory testing and quarantine measures for travelers.	Epstein et al., 2007; Hollingsworth et al., 2006
Surveillance and Early Detection	Establish robust surveillance systems to monitor the spread of disease, track outbreaks, and identify new cases promptly. Early detection allows for quick containment measures to prevent further transmission.	Briand et al., 2011; Ibrahim, 2020
Contact Tracing and Testing	Identifying and notifying individuals who have been in close contact with confirmed cases and encouraging them to get tested. Widespread testing helps in early detection and containment of the virus.	Mazza et al., 2021; Pozo-Martin et al., 2023
Vaccination Campaigns	Encouraging vaccination among eligible populations to build immunity and reduce the severity of the disease.	Angeli et al., 2022
Enhanced Hygiene Measures	Promoting regular handwashing, using hand sanitizers, and proper hygiene practices to reduce the risk of transmission.	Dalton et al., 2020; Irelli et al., 2020
Workplace/ School Schedule Changes	Implementing safety measures in workplaces and educational institutions, such as staggered shifts, remote work, and hybrid learning models.	Ferguson et al., 2006; Qualls et al., 2017
Public Awareness Campaigns	Educating the public about the importance of following guidelines and encouraging responsible behavior to control the spread of the virus.	Evison et al., 2021
Healthcare System Strengthening	Expanding healthcare facilities, ensuring an adequate supply of medical equipment and medications, and training healthcare workers to handle the increased patient load.	Cancedda et al., 2016; Kraef et al., 2020; Peiris et al., 2021
Economic Support	Providing financial assistance and support to individuals and businesses impacted by the pandemic to alleviate economic hardships.	Gholipour et al., 2023; Kurdin et al., 2020
Risk Communication and Transparency	Maintaining open and transparent communication with the public about the status of the pandemic, measures being taken, and any changes in guidelines.	Lowe et al., 2022; Menon & Goh, 2005; Zhang et al., 2020
Psychological and Social Support	Maintaining open and transparent communication with the public about the status of the pandemic, measures being taken, and any changes in guidelines.	Lowe et al., 2022; Menon & Goh, 2005; Zhang et al., 2020

6.3 Health System Performance Indicators

A health system performance metric or indicator (HSPI or simply, SPI), is an outcome of a pandemic mitigation intervention. The outcome may be intended vs. unintended or beneficial vs. adverse. SPIs occur at spatial scopes ranging from individuals to regionwide and may vary by the stakeholder type affected by the PMI (travelers, residents, shop workers, elderly, etc.); monetary vs. non-monetary, short term and long term, and so on.

Also, the SPIs may also be categorized in several ways, for example, via the sustainability pillars (Jeon & Amekudzi, 2005; Jeon et al., 2013; Jowitt, 2020): environmental, economic, and social, or the triple E's (Sinha and Labi, 2007): efficiency, effectiveness, and equity. In the context of health system performance, the economic sustainability includes: the governmental costs of vaccination programs, residents' out-of-pocket costs of medical treatment, the community (local businesses' shutdown-caused loss of income, and so on), and the social pillar includes equity in access to vaccination.

In PMI evaluation, SPIs are important because they help governments and health agencies carry out *ex ante* analysis of policies, programs and other interventions intended to control the pandemic. Also, SPI's can be used in an *ex poste* manner: to ascertain the extent to which the PMI have accomplished its goals during the pandemic. SPIs are often designed to reduce any bias or inconsistency in their indications of health performance. As such, for any specific PMI assessment problem, the chosen SPIs must have certain properties (Sinha and Labi, 2007; Labi, 2022).

- Appropriate: the SPI should reflect at least one goal of the PMI.
- Measurable: it should be possible the public health agency to use the SPI values to measure the impact of the PMI in a clear manner.
- Consistency: values of the SPI should be comparable across different spatial (location) or temporal spans.
- Relevant: the SPI should be a reflection of the perspectives of one or more stakeholders of the health system.
- Realistic: it should be possible to obtain data on the SPI easily
- Clear and concise. it should be easy to communicate the PMI impacts in terms of the SPI to any audience including non-technical ones.

Regarding pandemics, the literature contains a few SPI's for evaluating the PMI impacts. In the context of pandemic spread and severity, the SPIs commonly used include:

1. The number of persons infected in a given area or region.
2. The number of persons that exhibit symptoms of a given severity level.
3. The number of persons that pass away from the disease.
4. The rate of infections (ratio of the number to the total population).
5. The rate of symptom appearance of a given severity level (ratio of the number people exhibiting symptoms to the total population).
6. The rate of persons that pass away from the disease, that is total fatalities divided by some normalization metric, for example, fatalities per population; fatalities per exposed population, fatalities per vulnerable population and so on.
7. The number of people who transition of a higher level (infected) to a lower level (non-infected) of the disease.

6.4 The Measures of Effectiveness

A measure of effectiveness (MOEs) is a statistical parameter that describes the degree to which a PMI has achieved a health benefit (in terms of the SPI) to the public health system. An example of a statement that includes both concepts of SPI and MOE is:

> *"The disease fatality rate has reduced by 35% from last year due to vaccinations."*

In this statement, the SPI is the fatality rate, the MOE is 35%, and the PMI is the vaccinations. The MOE is often expressed as a statistical value (for example, a simple mean) in terms of a health SPI and helps gage the PMI's impact, e.g., infection rate reduction. The MOE may be short-, medium-, or long-term. Medium and long-term MOEs are important for assessing PMIs whose effectiveness is generally affected by the passage of time or the cumulation of a time-variant factor. Two of such time-variant factors are: virus resistance to medication; and technological obsolescence that renders the PMI incompatible with newer health system elements to which the PMI is functionally related (Labi, 2022).

6.4.1 Short-term MOE: Abrupt Jump of the Health System Performance

This is the simple difference between the SPI values just-before and just-after the PMI was applied.

6.4.2 Medium-term MOEs: Decrease in the Rate of Deterioration of the Health System

This concept refers to the extent to which the PMI slows down a rapidly deteriorating health system performance: the PMI causes the steep slope (a quickly deteriorating public health system) to a slope that is gentle (lower rate of deterioration). The health system performance is expressed in terms of the SPI.

6.4.3 Long Term MOEs

PMI effectiveness in the long term could be measured using any of the following statistics-based constructs:

(a) the PMI longevity, that is, after the PMI is implemented, how long it takes for the health system to deteriorate (that is, for the SPI to revert) to the pre-PMI implementation level of the health system's performance.

(b) the average SPI value several years after the PMI implementation.

(c) the average SPI value several years after the PMI implementation as a ratio or percentage of the SPI just before the PMI implementation.

(d) the increase in the area bound by the SPI-time function (line or curve) because of the PMI implementation, compared to the function corresponding to the scenario of no-PMI implementation.

(e) the PMI implementation's reduction in the probability that some threshold of health system adversity will occur for the first time (for example, disease-related deaths will reach a specific level), compared to such probability in the scenario with no-PMI implementation.

(f) the time (weeks or months) after the PMI implementation for first occurrence of a specific level of performance-related health system adversity.

Figure 6.2 illustrates some of these MOEs. Some of the MOEs use probabilistic methods including hazard or survivor functions, logistic modeling, and multinomial probit or logit modeling. For some of the MOEs, the effectiveness of a PMI could be measured against the performance of other similar health systems for which no such PMI was implemented at the same time.

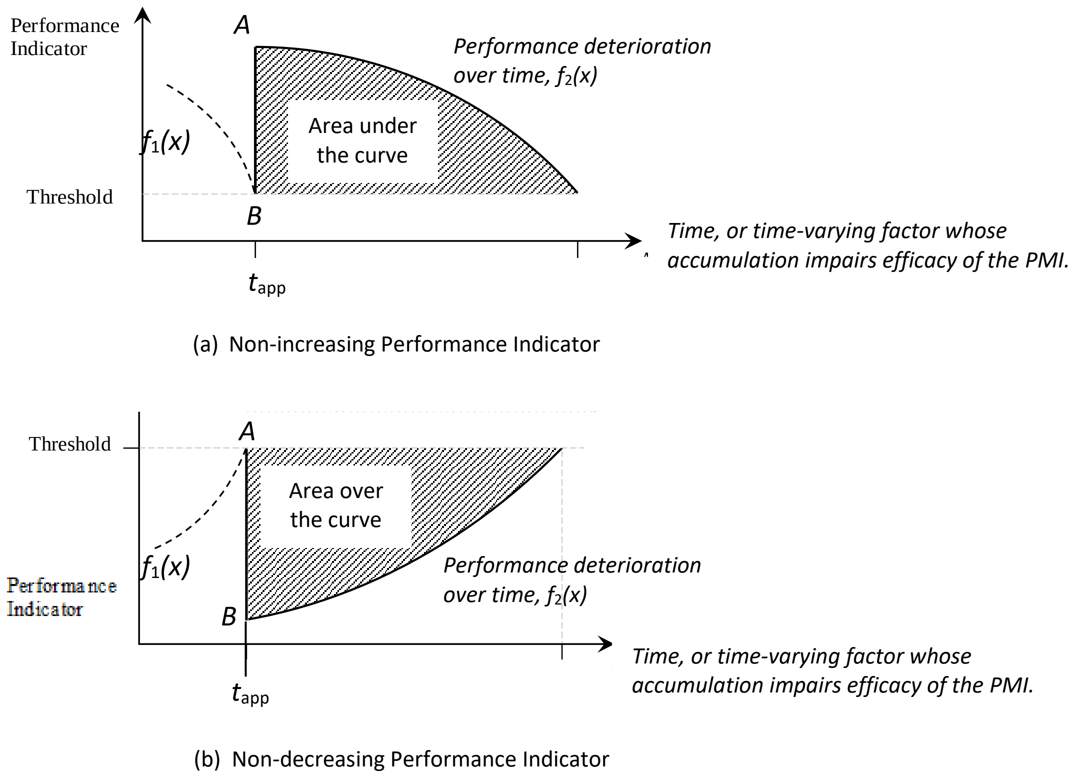


Figure 6.2 MOE graphical illustration based on SPIs with time-variant efficacy, t_{app} refers to the time of the PMI application (adapted from Labi, 2022)

6.5 Measuring and Modeling PMI Benefits (Effectiveness) using the SPI-based MOE

The effectiveness or benefit of a PMI can simply be defined as the extent to which it accomplishes the public health system's objectives regarding the PMI implementation. The MOEs expressed in terms of a health SPI can provide a specific quantitative statement of the PMI's effectiveness. Therefore, for assessing PMI effectiveness, what are needed include: (a) a good MOE and (b) a good SPI to serve as the basis for calculating the selected MOE. An MOE that is calculated based on a suitably-chosen SPI helps the public health agencies to identify the best interventions.

Three basic steps in effectiveness evaluation can be considered as (Labi, 2022): (a) How to measure the PMI intervention effectiveness, (b) In which SPI units to express the MOE, (c) was the PMI effective? (d) If the PMI was effective, how to model such effectiveness be modeled as a function of the factors related to: (a) the PMI, (b) the public health system, and (c) other aspects of the population (political affiliation, religion, demographics, and so on). This process involves choosing a good MOE for the PMI; calculating the MOE value in terms of the selected health SPI; assessing if the PMI was effective using the MOE values (that is, testing the hypothesis that the mean value of the MOE exceeds zero (in other words, the PMI was effective) vs. the null hypothesis that the mean value is statistically equal to zero (in other words, the PMI was not effective), at the given significance level. Considering the MOE distribution as a sampling distribution of the MOE means, then the hypothesis could be written as:

H_0: $m_{MOE} \leq 0$ (no statistically significant increase in the MOE due to the PMI), and

H_1: $m_{MOE} > 0$ (statistically significant increase in the MOE due to the PMI).

The rejection region for this 1-sided hypothesis is in the upper tail (Figure 6.3) and thus the test statistic's critical value is Z_a and calculated values are Z* which is calculated as $(m_{MOE} - 0)/(s/\sqrt{n})$. Subsequently, a statistical model could be developed to estimate the PMI effectiveness as a function of the variables related to the PMI and to the PMI's substrate, that is, the health system. In such a model, the MOE represents the response variable. The process involves the use of data collected from several similar populations or health systems that, in the past, had received the PMI in question.

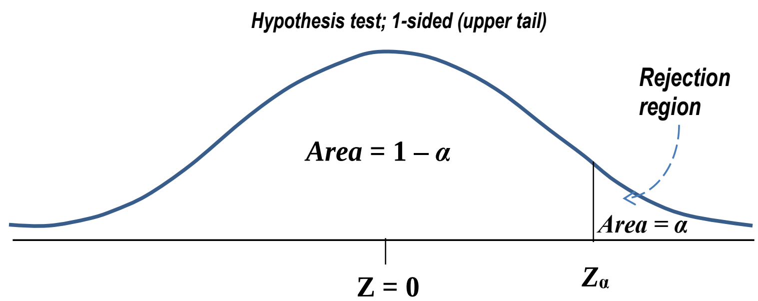


Figure 6.3 Testing hypothesis regarding PMI effectiveness

6.6 Discussion and Concluding Remarks

In future research that seeks to further develop constructs to measure PMI benefits to populations, researchers could view the entire problem setting through the lens of a health system that is not only integrated but also holistic, such that it includes various key components (pandemic response programs, availability and quality of health care facilities in the region, residents characteristics (vaccination-related beliefs, levels of education, age distribution, access to primary health care, and so on) and relationships between the components. As such, it will be useful to: define the spatial and temporal boundaries of the PMI impact in the context of the integrated health system, identify the stakeholders that will likely be affected, document the existing and target levels of the public health system performance, and identify the social, environmental and economic elements of sustainable development that are associated with the PMI's impacts that fall within the defined temporal and spatial boundary. In addition, it should be recognized that anticipated advancements in information and communication technologies, and innovations in health sciences and medicine, will generate new horizons in pandemic response in the form of increased opportunities to reduce the adverse impacts (indirect and indirect, monetary, and monetary) of pandemics and to increase the effectiveness of PMIs.

CHAPTER 7 CONCLUDING REMARKS, FOR PART I

7.1 Summary

Due to the close contact of passengers in transportation modes and the ease of mobility between different locations, transportation modes, particularly, mass transit, inherently provide highly infections environment in a pandemic. Therefore, transportation systems including hubs need special attention in terms of control policies and interventions. In the era of vehicle automation and connectivity the benefits of such technologies extend beyond traffic management to pandemic control. This study attempts to shed light on the opportunities of CAVs to foster safe and secure travel during a pandemic, to decrease the infection risk in a community.

First, this report presents a comprehensive literature review on epidemic modeling (Chapter 2) as it relates to transportation. In this regard, this report discusses some fundamental concepts in disease transmission and epidemic modeling and some attempts to control the COVID-19 pandemic. Then, a classification based on the epidemiologic modeling is presented. For each group of epidemic models, the relevant studies are reviewed. Then, the studies that incorporated transportation systems into disease transmission are reviewed.

Second, this report develops an epidemic model that captures the effects of transportation modes, specifically CAVs, on disease propagation (Chapter 3). The proposed model assumes a homogenous population that is divided into two main groups: travelers and non-travelers. The travelers make round trips between different trip zones by using the available transportation modes to do their activities. The non-travelers do not use any of the transportation modes and stay in their residential zones. The disease transmission occurs in three places: residential areas, transportation modes, and activity zones. In the disease propagation mechanism, four compartments are considered: susceptible, exposed, infected, and recovered. The proposed model is capable of incorporating different transportation modes with different capacities and disease transmission rates. Transportation authorities in conjunction with the public sector, can control disease propagation and pandemic by changing the capacity of CAVs, one of the transportation modes included in the model. The CAV's capacity to transport passengers is a decision variable for the transportation authorities and should be determined carefully. To do that, the study develops an optimization problem to determine the optimal capacity level for CAVs that yields the minimum number of infected people under a budget constraint and over a study period.

Third, the report discusses how CAVs can bring a safe mobility system to communities in a pandemic situation (Chapter 4). In this regard, the structure and concept of operation of CAVs to provide safe and clean mobility services are introduced. CAVs are driverless and equipped with proper ventilation systems, effective air filters, and UV lights. These features enable CAVs to decrease the infection risk on the side of vehicles. Regular sanitization of the inside of vehicles is another effective way to eliminate viruses, and CAVs should be equipped with that as well. Also, this report recommends the use of thermal cameras and microphone test devices to detect infected people with COVID-19 before boarding CAVs. In the second part of Chapter 5, the efficacy of the operation of CAVs in controlling a pandemic is investigated. The developed model in Chapter 3 is applied to a synthetic network that has different trip zones and conventional transportation modes that CAVs operate in to measure the effectiveness of CAVs in controlling a COVID-19 pandemic. In this regard, different numerical analyses, differing in the capacity of CAVs and social behaviors, are conducted, and the changes in the populations of susceptible, exposed, infected, and recovered compartments are presented. The numerical results show that serving passengers by CAV modes is indeed effective in reducing the number of exposed and infected people. Besides, the pandemic peak and duration are alleviated and reduced after introducing the CAVs to the transportation systems relative to a base case that has only conventional transportation modes. Furthermore, social behavior also affects the propagation of a pandemic in a community. The conducted experiments show that if recovered people adopt cautious and conservative behaviors to avoid getting infected again, the number of exposed and infected people decreases as well. Therefore, a synergy of social collaboration and transportation authority investments is very effective in controlling a COVID-19 pandemic. In practice, implementing CAV systems in transportation networks is costly for transportation agencies, and it might not be possible to replace the entire existing transportation system with CAV systems. Based on the optimization problem formulation developed in Chapter 3, a sensitivity analysis is conducted to shed light on the level of investment in CAV systems and the infected population in the community. It is shown that the more investments to increase CAV capacity will lead to fewer infections. More interestingly, the analyses show that, under a limited budget, serving the passengers of the modes with higher infection risks, even by serving a portion of the travelers on them (around 34%), brings a considerable portion of the prospective benefits of CAVs with full operation capacity.

Fourth, the report discussed a wide range of control policies and interventions that can be used to control a pandemic (Chapter 5). The discussed control policies and interventions were categorized into two main groups based on the type of disease. The first group of interventions is general and can be implemented in any type of pandemic. The second group of interventions and control policies is effective in mitigating airborne diseases.

Fifth, the report presents constructs benefits-measurement or effectiveness (MOEs) of pandemic mitigation interventions (PMIs) (Chapter 6). To do this, public health systems are considered engineering systems, and the relative concepts of engineering are applied. MOEs are expressed in terms of SPIs to help public health agencies measure the extent to which their PMI has achieved (or, is expected to achieve) the intended goals of the PMI in the short, medium, or long term. This can help the health system's managers effectively monitor the system performance, and to select and plan for optimal interventions for pandemic mitigation.

7.2 Findings and Conclusions

This report focuses on the efficacy of the operation of a proposed CAV system in helping to control a pandemic. This report shows that CAVs are potentially beneficial in decreasing the infection risk in transportation systems and ultimately decreasing the number of infected people. Proper airflow and ventilation systems are necessary to decrease the infection risk from airborne diseases. Also, using UV rays can eliminate the viruses existing inside vehicles. They should clean the vehicles after dropping off passengers. CAV systems are equipped with disease test devices, such as microphone tests for COVID-19, to detect infected people before boarding on CAV modes. Moreover, materials in CAV interiors can greatly affect the duration that the COVID-19 virus lasts. Selecting the right materials could eliminate almost all of the active viruses in an hour. Based on the proposed design and operation of CAVs, the study carries out analyses to measure the efficacy of CAVs in controlling a pandemic. The study results suggest that the operation of CAVs is indeed effective in controlling a pandemic by decreasing the number of exposed and infected people, relieving the pandemic peak, and shortening its duration. Also, increasing the capacity of

CAVs to accommodate more passengers improves these benefits in a community. Under a limited budget, serving the passengers of the modes with higher infection risks, even by serving a portion of the travelers on them (around 34%), brings a considerable portion of the prospective benefits of CAVs with full operation capacity. Furthermore, social behavior also affects the propagation of a pandemic in a community. The conducted experiments show that if recovered people adopt cautious and conservative behaviors to avoid getting reinfected, the number of exposed and infected people decreases. Therefore, a synergy of public health initiatives and transportation related policies can be effective in controlling pandemics.

7.3 Policy Recommendations

Based on the scope of this study, this report suggests several policy recommendations. In a pandemic, the development of effective analytical tools is essential to controlling the pandemic. It is suggested to policymakers and authorities to utilize or adapt the developed model of this study to predict changes in the propagation of diseases after implementing control policies and interventions. Second, authorities should develop practical plans to implement the control policies and interventions in advance, to be ready for any possible pandemic. The control plans should specify the timing, target groups, and details of interventions and control policies. Furthermore, highly infectious places should be detected and controlled with special policies. For example, this report showed that implementing CAV modes to serve mass transportation passengers is very effective in controlling a COVID-19 pandemic. This study shows that social behavior has a great influence on disease propagation in a community. In facing a pandemic, authorities should present people with some recommendations to adapt their social behavior to the pandemic. The recommendations for social behavior adaptation should be based on the type of disease and its transmission among the population. The adaptation recommendations should be promoted through education centers, the media, health agencies, and other related organizations. Moreover, this report discusses some initiatives and devices that have been shown to be effective in detecting infected people. Therefore, utilizing technology and advanced devices is another recommendation of this study. CAVs, as examples of emerging transportation technologies, are shown to be effective in controlling a pandemic by decreasing the number of exposed and infected people. Transportation agencies and city authorities should facilitate the adaptation of CAVs to the road and transit networks. Finally, appropriate measures of effectiveness (MOE) and health system performance indicators (SPIs) should be established. The MOEs and SPIs should align with the goals of the city and health authorities in the short, medium, and long term.

7.4 Suggestions for Future Research

The first chapter of this study can be extended in several directions. First, the developed epidemic model should be applied to a real network to investigate the effects of control policies and CAVs in realistic conditions. This requires calibrating the parameters of the proposed epidemic model based on real datasets and characterizing the transportation networks and mobility patterns. Second, an agent-based simulation model can be developed to predict the effects of control policies and the operation of CAVs in more detail. This report presents a population-based model that assumes a homogenous population captures the propagation of a disease in a community. An agent-based simulation model can incorporate different groups of people with different disease-related characteristics and social behaviors. This yields a more realistic picture of community behavior and disease propagation. The agent-based model can be used to simulate the behavior of travelers and disease transmission in transportation hubs, stations, and on the sides of CAVs. Third, a thorough financial analysis should be conducted on the investment and operation costs of CAV systems and the proposed control strategies. Such financial analysis could not facilitate cost-benefit analyses based on the operation costs of CAVs and the benefits of their operation in a pandemic.

Part II
CAVs and Disasters

CHAPTER 8 THE PROSPECTIVE ROLE OF CAVS IN DISASTER MANAGEMENT

8.1 Introduction

The emergence of the Connected and Automated Vehicles (CAVs) has been heralded for its prospective benefits in terms of safety, travel efficiency, transport productivity, and other impacts. In addition, CAVs offer benefits in times of pandemics, as discussed in earlier chapters of this report. In the context of disaster management, however, there appears to exist very few studies in the research literature regarding how CAVs could help in regarding not only infrastructure system operations but also society in general, in preparing for, withstanding, and recovering from disaster events. This is an important gap, because, throughout history, societies' efforts to escape (and to recover) from natural disasters have hinged on the efficiency of the extant transportation systems at the time of the disaster. There exists a plethora of past research on the role of transportation vehicles at the various phases of a disaster: pre-disaster, peri-disaster, and post-disaster. This chapter first reviews relevant literature about CAV uses in disasters, and then identifies and classifies the types of disasters. Then the chapter discusses the various stages of infrastructure system disruption during a disaster and identifies a number of ways to leverage CAVs not only to foster infrastructure resilience, but also to serve travelers during disasters.

8.2 A Review of Relevant Literature

A number of researchers have examined issues regarding the deployment of shared CAVs during disasters. A prescient article by Gilmore (1993) described a knowledge-based system for the control of multiple autonomous vehicles carrying out surveillance to facilitate emergency management during disasters. Gupta and Joshi (2022) argued that the sensors and cameras in a CAV can help identify the locations of any individuals in harm's way in a wide swath of area. Frackiewicz (2023) stated that autonomy is already being used in the transportation and logistics industries (to lower costs, increase productivity, and reduce human error) and that this technology could be deployed also in disasters, for vital deliveries to disaster areas safely and quickly without human input.

Ekram and Rahman (2018) used a microsimulation platform to analyze the impacts of CAVs on contraflow operations during emergency evacuations. Murray-Tuite et al. (2021), based on notions of voluntary release (by private owners) to government agencies for disaster management, examined public perceptions of CAV use in disaster management. Specifically, these authors gagged individuals' willingness to share their CAVs to help in evacuation efforts or in the transportation of disaster relief supplies and identified some concerns regarding such reluctance. Their study affirmed a proclivity of private CAV owners towards sharing their vehicles to support evacuation and disaster relief thereby potentially augmenting government response to disasters. The question, it seems, is whether emergency managers can rely on such public altruism in this regard or whether private CAVs should be commandeered by government for disaster emergency management. Lv et al. (2020) specifically investigated this question and analyzed the trade-offs between the benefits and costs of deployments of privately-owned CAVs during earthquake disasters and suggested that governments need to begin developing policies in this context.

8.3 Disaster Threat Types

In the context of civil engineering systems, disaster may occur due to any of several types of threats (Labi, 2014). Threat classification could be motivated by the realization of the existence of relationships (or in some cases, lack thereof) between the threat type and the impact on the prospective roles of CAV regarding the threat (disaster) response. For threat types that are associated with severe degradation of vehicle connectivity and/or autonomy, there is little advantage of using CAVs in the peri-disaster and post-disaster phases. Threats may be classified generally as external vs. internal (Figure 8.1).

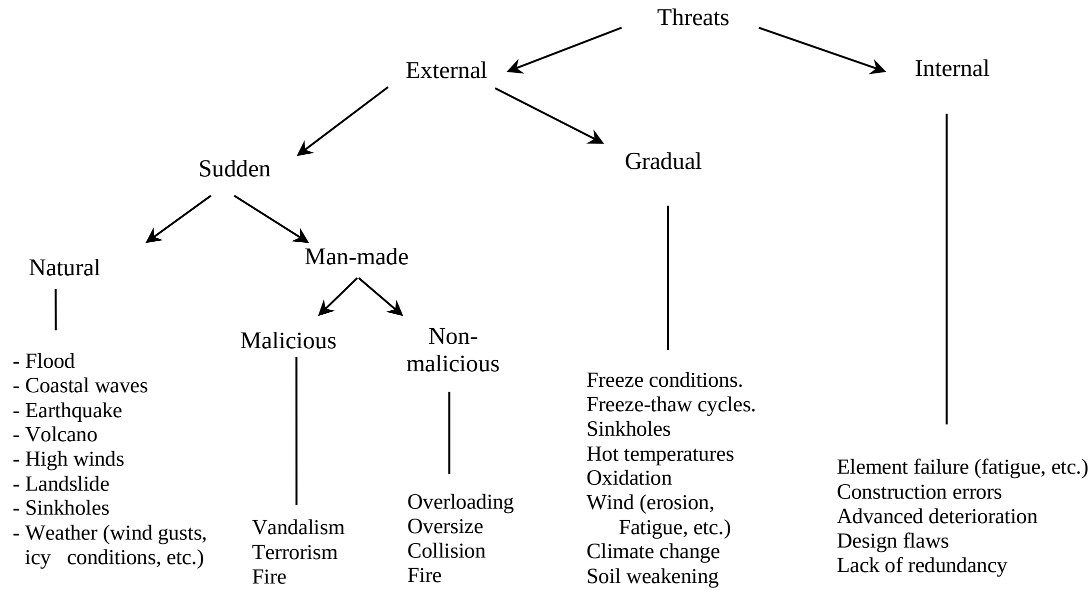


Figure 8.1 Civil-engineering related disaster threat categories and types that could affect vehicle automation and connectivity directly or indirectly

External threats may be sudden or gradual. Examples of sudden natural threats include earthquakes, floods, volcanoes, landslides, coastal waves such as tsunamis, high winds, and icy conditions in a winter storm. Also, examples of sudden man-made threats are vandalism and terrorism (which are intended) and overloading, collision, and oversize (which are generally not intended). Gradual external threats are often climate-related, and examples include freeze-thaw cycles, freeze or torrid conditions, oxidation, and wind action that may cause fatigue or erosion. Other gradual external threats include the corrosiveness of soil on which structures are founded, progressively weakening soils that cause gradual settlement of structures, air-laden salt in marine environments, and chemical application to deice roads at cold regions. Internal threats, which arise from within the infrastructure, often impair the structural integrity of the system. Examples include construction or design flaws, poor quality of construction material, repair delay of critical structural elements due to any of several factors –bending, shear, fatigue, poor design redundancy, corrosion, oxidation, and general age-induced weakening of structural elements.

Figure 8.2 provides illustrations of the types of threats that could affect vehicle automation and connectivity. The disasters shown in the photos could destroy the roadway image used to train the CAV algorithms, resulting in a “new” roadway environment that is unrecognizable by machine learning algorithms. Secondly, these disasters tend to destroy cyber infrastructure installed to support vehicle connectivity and automation, including traffic control devices, roadside units, and roadway sensors, thereby damaging the connectivity ecosystem. These disasters also impair the movements of CAVs that may be mobilized to assist in disaster response or recovery.

(a) Sudden, natural. Destruction of bridge after Hurricane Katrina, 2005.
(*Source: George Armstrong, FEMA, https://highways.dot.gov/public-roads/mayjune-2010)*

(b) Sudden, man-made. Interstate bridge collapse from truck collision with underpass, 2015, Indianapolis .
(*Source: Anon)*

(c) Sudden, natural. Landslide damage of Freeway 3, 2010, Keelung City, Taiwan .
(Source: D. Petley, blogs.agu.org/landslideblog)

(d) Sudden, man-made. I-80 bridge collapse from truck collision with underpass, 2007, San Francisco.
(Source: John Huseby, https://highways.dot.gov/public-roads/mayjune-2010)

Figure 8.2 Some types of threats to road systems: Certain disasters can (i) inherently result in a “new” roadway environment that is unrecognizable by the CAV’s machine learning algorithms; (ii) destroy cyber infrastructure installed to support vehicle connectivity and automation; or (iii) generally impair the movements of CAVs involved in disaster response or recovery.

8.3.1 Sudden Threats (Disasters)

Sudden threats are those that often occur with little or no warning, and often lead to injury or the loss of life of the road users. These include natural threats (earthquakes, flooding, landslides, and sinkholes) and anthropogenic threats (terrorism, overloading, collision, and oversize).

<u>(a) Earthquakes</u>

Earthquakes happen when geological fault rupture and volcanic activity causes the Earth's crust to release sudden bursts of energy. This creates seismic waves that cause shaking and ground displacement at the Earth's surface along the fault line. The local amplification of ground movement causes damage to subterranean and surface infrastructure systems including subways and roadways. Earthquakes represent a unique type of threat to road systems because they often catalyze other types of threats that also threaten travel safety and mobility. For example, when an earthquake occurs in the sea, displacement of the seabed can cause waves of increasing amplitude as it moves away from the epicenter until it reaches land as a high wave or tsunami that often floods coastal roadways. Earthquakes could also lead to landslides, and in certain cases, volcanic activity. The connectivity feature of CAV could be useful in the post-earthquake (communication and traffic stabilization during evacuee return and recovery efforts). The automation feature of CAV could help in delivering supplies to stranded populations at minimal risk (as there is no human driver).

<u>(b) Severe weather</u>

Weather can be defined as the short-term (minutes, days, or weeks) variations of the atmospheric conditions, including temperature, humidity, precipitation, cloudiness, visibility, and wind. Weather impairs the operational performance of transportation systems and in extreme cases such as high winds, can cause physical damage to the structure through sudden collapse or fatigue (Figure 8.2). In 2018, Hurricane Florence led to severe flooding of the transportation systems in the Carolinas. During Hurricane Katrina in New Orleans in 2005, several hundreds of people lost their lives due to inadequate access to transportation services; also, in 2017, seven million people struggled to escape Hurricane Irma in Florida (Disaster Recovery, 2023). This led to traffic jams and other related issues.

The automation feature of CAV could help increase transportation access to the infirm and the elderly and general traffic throughput at disaster areas. CAVs could also help shepherd vehicle traffic during evacuation (pre-flood) and return (post flood), and during the flood, could be used to deliver supplies to stranded populations at minimal risk (as there is no human driver). It has been argued that deploying swarms of CAVs (and drones) in the affected region would free up other resources for the emergency management IOO (Disaster Recovery, 2023). The connectivity feature of CAV could be useful in pre-flood (assessing the geographical and temporal scope of flooding and flood depth evaluation and communication; evacuation from flooded areas), peri-flood (monitoring flood expansion or retreat), and post-flood (communication and traffic stabilization during evacuee return and recovery efforts).

<u>(c) Flooding</u>

Flooding occurs when rivers or lakes become swollen with excess runoff from rain or when rainwater accumulates on soil that is already saturated, or when sea water levels rise above the heights of coastal protection structures. Flash flooding in a river basin may also occur due to the sudden release of water from an upstream dam as recently observed in the Kakhovka Dam in Ukraine. Rising water levels have been observed globally and this could be a part of a long-term trend. Low-lying cities currently at the risk of flooding disaster due to sea level rise include Rotterdam, Dhaka, New Orleans, and Venice. According to the Intergovernmental Panel on Climate Change (IPCC, 2007), the worldwide mean sea level rose at an average rate of 1.3-2.3 mm/year since 1961; and increased to 2.4-3.8 mm/yr in the 1993-2003 period. The connectivity feature of CAVs could be useful during:

- pre-flood activities (assessing the geographical and temporal scope of flooding; flood depth evaluation and communication; evacuation of humans from flooded areas),
- peri-flood (monitoring flood expansion or retreat in real time), and
- post-flood (communication, lane management, and traffic stabilization during evacuee return and recovery efforts).

In addition, the automation feature of CAV could help in shepherding traffic flows during evacuation (pre-flood) and return (post flood), and during the flood, could be used to deliver supplies to stranded populations at minimal risk (as there is no human driver).

<u>(d) Landslides</u>

A landslide, a slowly forming but suddenly occurring disaster, is a geological phenomenon at mountainous areas that involves slope failure and gravity-induced flow of shallow debris . This often causes full or partial blockage of highways and bridges in mountainous areas impair traffic mobility and safety. Landslides can be triggered by natural events (such as increased moisture content due to prolonged rainfall) or anthropogenic actions such as vibration from construction or mining equipment, deforestation, and foliage clearance, and land cultivation practices that destabilize fragile slopes (Beniston, 2004; Sassa and Canuti, 2008). Landslides often cause harm directly to motorists at the time of they occur (due to falling rocks), and often lead to road blockage that degrades road safety and mobility, and network connectivity and local access. The connectivity feature of CAV could be useful in pre-landslide phase (assessing the risk (or occurrence) of landslides at road sections and communicating this information to IOOs and road users; identification of alternative routes before or after the landslide), post-landslide (monitoring and communicating the congestion and safety effects of the blocked road.

<u>(e) Suddenly occurring anthropogenic threats</u>

Anthropogenic threats are more difficult to manage compared to natural threats. Further, of the anthropogenic threats, the malicious kind (terrorism and vandalism) are even more challenging to predict compared to the unintended kinds. Factors that could influence the likelihood of malicious man-made threats to a specific infrastructure include commerce-related factors (traffic volumes), iconic nature of the infrastructure, and the role of the infrastructure in system in military operations. In the literature, there exists methods for assessing infrastructure vulnerability to man-made threats (Rummel et al., 2002).

Also, there exists unintended threats of infrastructure **overloading**. Most infrastructure are designed to handle a certain capacity. Some types of infrastructure suffer little or no physical damage when demand exceeds capacity while other system types fail or suffer serious damage when they are overloaded. Bridges rarely fail suddenly upon the first instance of overloading; rather, it is a series of overloading events that gradually culminate in some mode of failure, such as shear, bending, or fatigue in the bridge elements, which, if not detected through regular inspections, ultimately leads to some damage or in extreme cases, destruction of the structure through catastrophic failure. There are also the threats of **collision**, as road infrastructure systems are always prone to accidental damage from the road users or to activities that occur in the proximity of the road system.

8.3.2 Drawn-out Threats

Drawn-out threats are those that occur slowly over time and may even go unnoticed or considered insignificant until they evolve into sudden (and often, catastrophic) failure of the infrastructure involved. The surreptitious nature of these types of threats is what make them particularly hazardous. These threat types include erosion, scour, sedimentation, threats related to climate (freeze conditions and cyclical freeze-thaws, heat), weather (e.g., winds), internal fatigue or design flaws, poor condition due to infrastructure aging and wear-and-tear, vandalism of the infrastructure, and theft of infrastructure components.

(a) Incipient threats related to climate change

Climate is the average of conditions experienced over an extended time period (typically, 30 years) and compared to weather, is a more formidable threat to the long-term durability of civil system physical structures. The threats related to climate include freeze, freeze-thaw, oxidation, and warm temperatures. Freezing conditions in wintertime cause materials to become brittle and prone to cracking, and cause ice lenses in soils which leads to soil heaving upon thawing during the spring season. Freeze-thaw transitions, often experienced in the early and late phases of winter, cause expansion and contraction of materials that can lead to failure. In the very long term, the threats posed to infrastructure occur in the form of climate change because systems that are designed for a certain climatic condition could become inadequate when these conditions change.

(b) Design- and maintenance-related disasters

Internal fatigue or design flaws have often caused infrastructure failure and loss of life. Fatigue failure occurs when a road infrastructure component material is undergoes repeated loading and unloading until the component fails , often with minimal warning. Also, design errors or incorrect specifications could threaten the physical or operational integrity of infrastructure. For example, designs that do not accommodate adequate redundancy can lead to sudden life-threatening failures of the system as was experienced in the I-35 bridge in Minnesota in 2007. Regarding the issue of inadequate maintenance, several countries have infrastructure assets built several decades ago but inadequate maintenance has left them vulnerable to future environmental and usage load related hazards.

(c) Vandalism, theft, and other threats

Vandalism can be described as the intended or malicious destruction or damage of property. For an infrastructure, this includes damage or removal of parts of the system including lighting, electrical, and mechanical components and spray painting and graffiti defacement. Theft (often referred to as acquisitive vandalism (Cohen 1973)) is the unauthorized removal of parts of civil engineering system, often with the intention to use or sell for profit. While such acts rarely cause complete destruction of a system or jeopardize its structural strength, it can cause aesthetic or operational problems. For example, theft of metal barriers that constitute highway guardrails can lead to impaired function of these systems and could lead to greater severity of crashes that occur at such locations.

In some urban areas, vandalism and theft pose serious threats to the operations of civil engineering systems, and laws are specifically enacted to combat such social menaces. Fire, intended (arson) or unintended, can cause serious damage or complete destruction of infrastructure, particularly when the system is not designed adequately to accommodate high temperatures. Similar to climatic high temperatures, fire can cause materials such as steel and reinforced concrete to buckle, enter plastic phases of deformation, and even melt in extreme cases.

8.4 Stages of Infrastructure System Disruption

CAVs can be useful at the various stages of systems disruption. Edwards (2009) and Brunner and Giroux (2009) presented a 4-stage model for systems disruption and resilience applications at each stage (Figure 8.3) and Sheard and Mostashari (2009) presented a similar five-stage model for the disruption of infrastructure and the resilience activities at each stage (Figure 8.4). Also, the Resilience Engineering Network (2007), Hale and Heijer (2006), Westrum (2006), Hollnagel et al. (2006), and Gunderson and Protchard (2002) provide some resilience-enhancing activities at each stage of the disruption process, and CAVs could be leveraged to help in these activities.

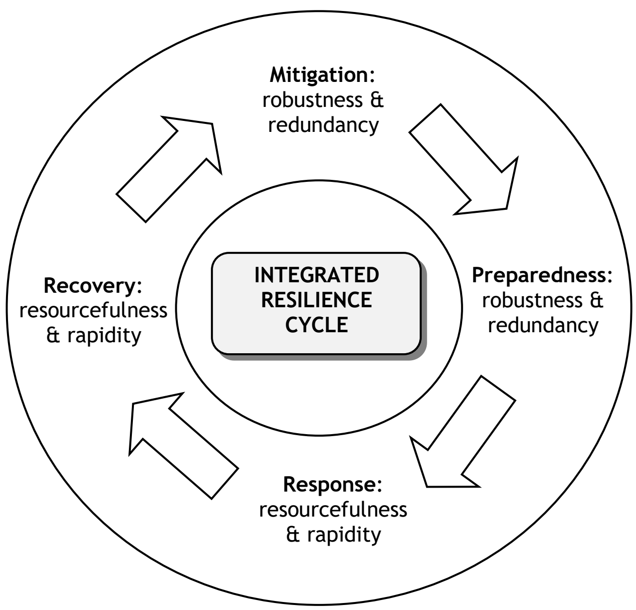


Figure 8.3 Four-stage model of system disruption and resilience considerations at each stage Edwards (2009) and Brunner and Giroux (2009)

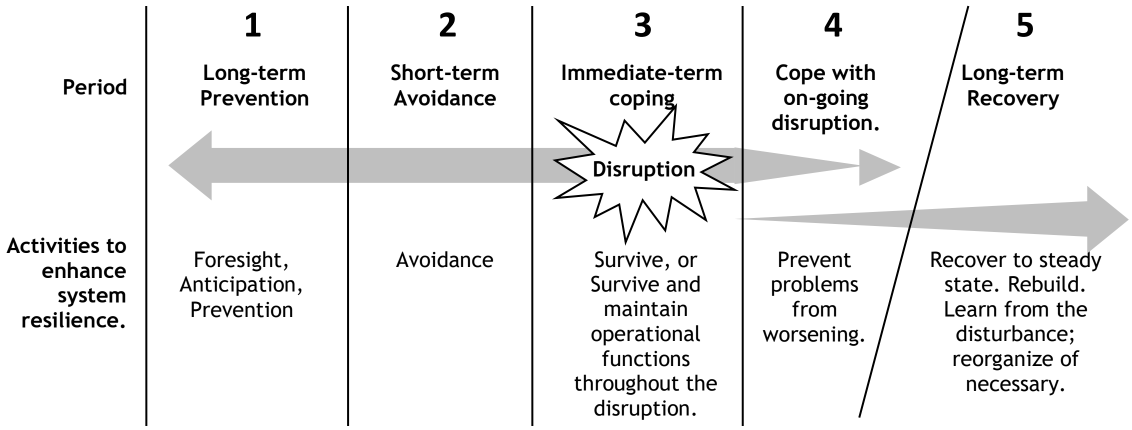


Figure 8.4 Five-stage model of system disruption and resilience considerations at each stage (Sheard and Mostashari, 2009)

8.4.1 Preparedness (before the disruption)

Actions by IOOs to promote resilience include the development of analytical or simulation models that help predict the occurrence and intensity of the disruption. With such knowledge, the IOO is placed in a better position to anticipate or plan for disruptions, prepare the community in order to reduce the exposure, and equip itself with the necessary resources to prevent or reduce the loss of control during the disruption. Where the threat occurrence is deemed to be inevitable, the infrastructure IOO makes efforts to prevent the disruption by eliminating the threat; where elimination is impractical, the engineer makes efforts to enhance the system resilience by increasing the system's physical strength or capacity in anticipation of the disruption. Also, at this stage, the IOO prepares the community and system users and takes the necessary proactive measures to minimize exposure and thus reduce casualties or inconvenience due to the disruption. This includes efforts to keep information systems, social network resources, and other communication tools up to date. The Sheard and Mostashari (2009) model breaks up Edwards (2009)'s preparation phase into two phases: long term and short term.

8.4.2 Response (during the disruption)

During the disruption, the purpose of enhancing resilience is to increase survival and to reduce casualties or inconvenience during the disruption. In certain cases, the IOO or operator is required to keep the system functioning during the disruption and subsequent recovery; therefore, both the physical and operational resilience are to be ensured. At this stage, the IOO addresses problems associated with the disruption. Often, these are sudden problems that pertain to the operational integrity of the system; in other cases, they pertain to physical damage that must be repaired in order for operational performance to be restored. It is often the case that a system must be resilient enough to operate continuously throughout the disruption, albeit with a lower level of functionality. A resilient system, therefore, is one that responds or reacts quickly and efficiently to disruptions, is able to recover from loss of control, and is robust enough to resist adverse situations or stimuli that could impair its functionality. Not only must the system be resilient enough to survive the disruption, but it must also prevent a bad situation from becoming worse. To do this, the resilient system must be capable of enduring adverse situations during the disruption, and the IOO will need to carry out continuous monitoring of the situation to identify and address other threats or to exploit opportunities that emerge during the disruption. It can be argued that CAVs can represent an unprecedented enhancement to present-day evacuation programs and plans. At the pre-disaster (and in some cases, the peri-disaster stages), CAVs provide critical mobility particularly for the vulnerable segments of populations – those who cannot afford to purchase or rent a vehicle, and those who cannot drive such as the elderly and others with special mobility needs.

8.4.3 Recovery (after the disruption)

The biggest challenge that IOOs face is the restoration of their systems after disruptions. Depending on the type of system and the nature of the disruption, the recovery may take weeks, months, or even years. Also, a concern is that for a long period of time, the restored physical or operational state may be inferior to the state before the disruption. In many cases, an IOO is able to convert the damage occurrence to an opportunity to increase the system's physical condition or capacity to a higher level sooner than the pre-disruption target date for such improvements. A good way to imagine the term "recovery" would be the capability of a rubber ball to return to its original shape after a force is removed (Jackson, 2009). To enhance system resilience, the IOO must carry out activities that help the community as well as the system to recover from the disruption. The IOO must recognize and learn the appropriate lessons related to the reliability of prediction of the threat occurrence and magnitude, the reduction of community exposure, and the adequacy of the system resilience. This knowledge will assist the IOO in becoming better prepared for future similar threats. At this phase, CAVs could assist in assessing the extent of damage, identifying routes for emergency vehicles, and medical deliveries (Disaster Recovery, 2023).

8.4.4 Mitigation (after the disruption)

Mitigation includes learning the lessons from a previous similar disruption and making plans for long-term prevention.

8.5 Leveraging CAVs to build infrastructure resilience to serve populations during disasters.

At any of the stages of resilience discussed above, both operational and physical resilience could be enhanced by using CAVs, in any of several contexts as discussed below.

8.5.1 Quantification of Threat

The first step in increasing the resilience of infrastructure is to identify the possible threat types and their intensities, and establishing how the CAV could help build operational resilience on the infrastructure at all phases of the disaster (threat manifestation), and how to measure the effectiveness of any CAV-related or other interventions for resilience enhancement.

8.5.2 Information systems

The transportation or infrastructure IOO must establish a comprehensive database related to the region or local environmental in question; the threat type and its possible locations, and exposure; the possible interventions that could be applied; and the potential cost and benefits (effectiveness) of the intervention.

8.5.3 Effective communication

Infrastructure systems can be made more resilient when they have an effective communication system and strong social network that collect, manage, and disseminate critical information related to the system operations during and after the disruption. CAVs can help play these roles by virtue of their connectivity feature. In certain cases, there could be cellular network failures due to the disaster, and in such cases, CAV connections to satellites for communication protects communication resilience. In addition, CAVs have the capability to generate or receive real-time information on road and traffic conditions at all stages of the disaster. Such information includes the locations of safe routes or evacuation routes, and locations and status of evacuation centers (Disaster Recovery, 2023).

8.5.4 CAV-related resilience-oriented design and operations

Where the critical components of an infrastructure system (i) are self-correcting and repairable, (ii)possess in-built redundancies, and (iii) are autonomous and fail-safe, their resilience is increased. Autonomy refers to the situation where the failure of any one component of the system does not contribute to failure of other components; and fail-safe is the situation where failure of a component causes it to automatically shift to its most benign form. These attributes assure that decisions are not only incremental but also reversible; that way, costs are minimized if a specific decision is found to be ineffective or even unsafe. To enhance system resilience, it has been recommended that prior to the occurrence of any disruption, the IOO must be capable of reliably predicting the changing trends of risk as well as the risk factors (REN, 2012). The above examples are general principles for increasing the resilience of infrastructure. The specific strategies will differ across system types in the different infrastructure disciplines. In the general field of transportation engineering a number of strategies that can increase the resilience were presented by ECONorthwest and PBQD (2002), Husdal (2004), and other sources, and these could be enhanced using CAV capabilities:

- increase the diversity of available transportation modes by ensuring that adequate opportunities exist for people to use other forms of transportation (this may include cycling, walking, carsharing, ridesharing, and traveling by transit, and CAVs).
- increase the redundancy and connectivity of the area’s transportation network; promote standards for system design and construction to withstand extreme natural or operating conditions.
- improve monitoring systems in order to quickly identify problems before they occur, including physical damage, demand surges, unsafe operating conditions, and other risks (these can be facilitated by the autonomous and connectivity capabilities of CAVs)
- improve monitoring systems in order to quickly identify problems before they occur, including physical damage, demand surges, unsafe operating conditions, and other risks.
- The V2X capability of CAVs can facilitate communication among CAVs serving the evaluation process, roadway infrastructure, IOOs, EMAs, evacuation centers and shelters, and other residents. Information to be shared include infrastructure physical conditions (flood depths, bridge structural integrity, and so on) and operational conditions (congestion and flow volumes at various links in the network) and the occupancy status at evacuation centers and shelters. According to Boswell and Riggs (2017), a lesson from the 2017

California wildfires was the failure of existing public safety systems not only to warn of the disaster but also to ensure safe evacuation of residents.

Other ways by which CAVs could help serve populations during disasters include:

- Provide an alternative means of transportation for "socially vulnerable persons" who cannot not afford to purchase a private vehicle, or where the IOO or EMA has no public plan to deploy some form of mass transportation for evacuation (Disaster Recovery n.d.).
- Deliver relief supplies to shelters where human drivers may find it too risky to access.
- Provide mobility services in cases where human drivers may be too tired to drive safely, or to traumatized or emotionally spent to drive.
- Boswell and Riggs (2017) discussed the possibility that EMAs could establish a fleet of CAVs purposefully for disaster evacuation. Recognizing the scale of typical evacuations, and the low likelihood that AVs will be set aside just for evacuation purposes, the authors suggested that such AVs would likely also serve as a regular part of a rideshare company's shared fleet.

8.5.5 Other desirable CAV design aspects for disaster management

CAV design features that could help in disaster management could have the following design aspects:

<u>All terrain chassis:</u> The CAV could designed for navigating earth tracks, light bush, and other unstructured roads and in areas of low visibility (Boswell and Riggs, 2017). This can enable the CAV to travel to areas inaccessible using HDVs and other traditional modes of transportation (Frackiewicz, 2023).

<u>Disaster materials</u>: A CAV built using materials that protect its operations in conditions associated with the disaster, is more capable of a standard HDV. For example, in fire disasters, CAV body parts built non-combustible materials can help it withstand high temperatures; in flood disasters, CAVs will be capable of amphibious operations if they contain air compartments to facilitate floating or navigation in shallow or deep waters.

<u>Autonomy and connectivity:</u> The CAV could be made to have adequate numbers and types of sensors that can help it navigate difficult areas. vehicles must be able to navigate complex terrain, identify obstacles, and avoid collisions. Frackiewicz (2023) inferred that, unlike HDVs, CAVs generally have greater capability to respond to changing environmental conditions such as inclement weather and other external conditions. This is possible because CAVs possess V2X capability that can help it communicate with other vehicles and all other agents and entities needed for navigating difficult areas. Through such connectivity, CAVs can transmit disaster-related data securely and quickly among vehicles and fixed infrastructure (such as a central operations center).

8.6 Discussion

Frackiewicz (2023) expressed optimism that as CAV technology continues to evolve, it will become an increasingly important component of disaster relief and emergency response operations globally. The information in this chapter can help departments of transportation and emergency management agencies in preparing for mass evacuation (in pre-disaster stages) using CAVs to assist evacuation of individuals at critical transportation need households (CTNH).

Part III
Closing Chapters

CHAPTER 9 SUMMARY OF STUDY EFFORT

The first part of this study addressed CAVs and pandemics. This discussion hopefully shed some light on the operation of CAVs during a pandemic to decrease the infection risk in a community. In this regard, a literature review on the fundamental concepts of epidemiologic modeling was presented, and a population-based epidemic model was proposed to capture the effects of transportation initiatives (including new “modes” such as CAVs) on infection risk disease and propagation. The proposed model can incorporate different transportation modes that have different capacities and disease transmission rates.

Next, the report discussed a wide range of disease control policies and interventions that could help minimize the spread of a pandemic. Then the report introduced the features, structure, and operational concept of specially designed CAVs that provide safe and clean mobility services. The prospective efficacy of these special CAVs in controlling a pandemic was investigated using the proposed epidemiologic model, and this was demonstrated using a synthetic transportation network in the specific context of the COVID-19 pandemic. The report then proposed different measures or metrics that could be used by transportation and health agencies to assess the effectiveness of transportation-related pandemic control policies and interventions which include the use of special CAVs during pandemics to support travel needs.

The second part of this study focused on how CAVs can be utilized in disasters. After presenting a synthesis of relevant literature on this subject, the report identified the various types of disasters and discusses the various stages of infrastructure system disruption during a disaster. Finally, the report identified ways to leverage CAVs not only to build infrastructure resilience but also to serve populations during disasters.

CHAPTER 10 SYNOPSIS OF PERFORMANCE INDICATORS

10.1 Part I of USDOT Performance Indicators

Over the study period for this project, three (2) transportation-related courses were offered that was taught by the PIs.. Two graduate students, two visiting scholars, and two post-doctoral researchers participated in the research project during the study period. During the study period, one (1) transportation-related advanced degree (doctoral) program and one (1) transportation-related M.S. program utilized the CCAT grant funds from this research project to support the two graduate students.

10.2 Part II of USDOT Performance Indicators

Research Performance Indicators:
The work from this applied research project was disseminated to an estimated total of 120 people in attendance (from industry, government, and academia) through three (3) presentations at: the NGTS conference; ASCE International Conference on Transportation & Development, and Purdue's Annual Road School.

Leadership Development Performance Indicators:
This research project generated 1 academic engagement and 1 industry engagement. The PIs held positions in 2 national organizations that address issues related to this research project. The two post-doctoral researchers hold positions in TRB committees related to the subject of this research.

Education and Workforce Development Performance Indicators:
The methods, data and/or results from this study were incorporated in the syllabi for the Spring 2021, Fall 2021, Spring 2022, and Fall 2022 versions of the following courses at Purdue University:
(a) CE 561: Transportation Systems Evaluation, a mandatory graduate level course at Purdue's transportation engineering graduate programs (average 10 students at each course offering),
(b) CE 299: Smart Mobility, an optional undergraduate level course at Purdue' civil engineering B.S. program, (average 12 students),
(c) CE 398: Introduction to Civil Engineering Systems, a mandatory undergraduate level course at Purdue University's civil engineering program, (average 85 students at each course offering).

The methods, data and/or results from this study will also be incorporated in future versions of the courses stated above. Students from these courses will soon be entering the workforce. Thereby, the research helped enlarge the pool of people trained to develop knowledge and utilize at least a part of the technologies developed in this research, and to put them to use when they enter the workforce. Based partly on a recognition of his contributions to this study, one of the post-doctoral researchers on this project earned a faculty position at the Illinois Institute of Technology in Chicago. The other post-doctoral researcher earned a faculty position at the University of Wisconsin, Madison.

The outputs, outcomes, and impacts are described in Chapter 11.

CHAPTER 11 STUDY OUTCOMES AND OUTPUTS

11.1 Outputs

11.1.1 Publications, conference papers, and presentations

Presentations

Pourgholamali, M., Sharma, A., Ye, Z., Arefkhani, H., Dietz, J. E., Labi, S. (2023). Public health benefits of connected and autonomous vehicle services during a pandemic: An epidemiologic analysis, *108th Annual Purdue Road School Transportation Conference & Exposition, March 13-15, 2003,* Purdue University, West Lafayette, IN.

Pourgholamali, M., Sharma, A., Ye, Z., Arefkhani, H., Dietz, J. E., Labi, S. (2023). Public health benefits of connected and autonomous vehicle services during a pandemic: An epidemiologic analysis, *Next Generation Transport System (NGTS), West Lafayette, IN.*

Pourgholamali, M., Sharma, A., Ye, Z., Arefkhani, H., Labi, S., (2023) Epidemiologic-based Modeling of the effectiveness of transportation-related pandemic control policies; a comparison in CAV and traditional eras, *ASCE International Conference on Transportation & Development*, Austin, Texas, June 14-17, 2023.

11.1.2 Other outputs

One of the PIs and one researcher of this study, and two cost share collaborators served as guest editors of a special issue in the *Frontiers in Built Environment* journal, where they edited a collection of articles on Automation, Connectivity, and Electric Propulsion. Their special journal issue editorial is published with the following citation:
Labi, S., Anastasopoulos, P., Miralinaghi, M., Ong, G.P., Zhu, F. (2021). Editorial: Advances in Planning for Emerging Transportation Technologies: Towards Automation, Connectivity, and Electric Propulsion, Frontiers in Built Environment 7, 666246.
https://www.frontiersin.org/articles/10.3389/fbuil.2021.666246/full

No policy papers have yet been produced from this research, and no website has been developed yet for the outcomes of this research. The research produced a framework that could be used by transportation administrations, health agencies, and departs of homeland security (particularly at the local level of government) to leverage vehicle automation and connectivity to minimize infection risks during pandemics, and to mitigate and monitor travel and other conditions associated with disasters. The research outcome (framework, methodology, analytical models, and case study) can be used in undergraduate and graduate courses or curricula related to transportation, public health, and homeland security.

11.2 Outcomes

This project produced outcomes that could influence public agencies' policies and preparation plans during pandemics. These are:

- Increased understanding and awareness of the vehicle automation and connectivity features and their prospective role in pandemic control and disaster management,
- More reliable and robust long-term transportation planning and travel policies (particularly by urban road agencies) that account for pandemic control and disaster management.

11.3 List of impacts

The impacts of this project are expected to be manifested through the effects of its outcomes on the transportation system, or society in general, during times of the adverse events of pandemics and disasters. This includes how the research outcomes could potentially improve the operation and safety of the transportation system during these two adverse events, increase the body of knowledge and technologies, enlarges the pool of people trained to develop knowledge and utilize new technologies and put them to use, and improve the physical, institutional, and information resources that enable people to have access to training and new technologies. A list of specific impacts from this research project, are as follows:

- Support for the application of vehicle automation and connectivity in efforts to combat pandemics or in efforts to mitigate the effects of disasters.
- Stronger justification for highway agencies, public health offices, and homeland security departments to make investments (or to make policies that incentive the private sector to make investments) in infrastructure that support transportation related automation and connectivity.
- The two graduate students that worked on this project will enter the workforce in 2024 to help support the workforce that will implement the new technologies developed in this study in the transportation, public health, or homeland security sectors.
- The project had some impact on education, as parts of the research outcomes were incorporated in two undergraduate and one graduate level course at Purdue University. The students on these courses, who will soon be entering the workforce, benefitted from these courses. This helps enlarge further the pool of people trained as part of this research project to develop knowledge and utilize the technologies developed in this research, and to put them to use when they enter the workforce.

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