Vitality recovery of major Japanese railway stations under COVID-19

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Abstract

The COVID-19 pandemic has severely disrupted the public transportation (PT) system, and it is a challenge to assess the extent of its impact. Due to the broader concept of demand and the difficulty of measuring its changes directly, this research introduces a comprehensive concept, ‘vitality’, to demonstrate the changes in the movement of people at stations during the COVID-19 pandemic. In this research, ‘vitality’ is the population of people staying in the station area over a period of time. Vitality can be influenced by a variety of factors such as commercial activity, major events, station accessibility and overall functionality, and most importantly, passenger ridership. It reflects the multifaceted nature of station activity and provides a more comprehensive measure of station dynamics than traditional ridership metrics. The focus on vitality is a major contribution of this research.

In this research, major railway stations in Japan have been selected to provide an in-depth analysis of the multiple impacts of the pandemic on the public transportation system, including the possible outcomes of the policies and the responses from operators. Possible common factors between stations with different levels of impact are analyzed, trends in station vitality in the context of the pandemic are predicted using different methodologies, and finally, some suggestions are made on how to balance the level of public transport service with operating costs from the operator's perspective.

This research has two main objectives. Firstly, it aims to understand the patterns of changes in station vitality and the influencing factors during a pandemic by analyzing comprehensive data from major Japanese rail stations. Secondly, it addresses the trade-offs between service quality, operational constraints, and long-term demand. By evaluating forecasting methods and developing adjustment plans, it provides PT operators with insights to balance service continuity and retain demand in the post-pandemic period.

The introduction underscores the critical need to address the repercussions of COVID-19 on PT, detailing the primary objectives and the structure of this research. A thorough literature review examines the pandemic's diverse effects on PT, emphasizing shifts in ridership patterns, operational challenges, and the implications for transportation planning and management. Methodologies for data collection and analysis are meticulously reviewed, underscoring the pivotal role of accurate and timely data in effective demand forecasting and strategic planning.

A novel analytical framework is introduced, integrating the 4R theory (Robustness, Redundancy, Resourcefulness, and Rapidity) to outline PT operator responses to the pandemic. This framework considers a range of factors, including institutional, physical, social, economic, and environmental dimensions. Advanced station clustering techniques analyze short- and medium-term changes in vitality, identifying key predictors of recovery and stations experiencing significant declines.

Multinomial regression models elucidate the impact of land-use factors on station vitality, highlighting how variables such as point of interest (POI) density and land-use types influence station dynamics. Results indicate that the number of service lines and the local population ratio significantly impact demand loss, while other factors like population density and proximity to major cities have varying effects.

For long-term demand forecasting, ARIMAX and LSTM models are employed to predict post-COVID demand trends. The ARIMAX model, incorporating external variables like COVID-19 cases and policy measures, shows higher accuracy in forecasting demand patterns. The LSTM model, though requiring substantial training data, excels in capturing complex demand trends, aiding PT operators in optimizing service frequencies and resource allocation.

The strategic framework underscores the necessity for flexible frequency planning to ensure resilience and sustainability. The analysis emphasizes maintaining service levels that can adapt to fluctuating demand, minimizing financial instability risks for operators during prolonged crises.

In summary, the COVID-19 pandemic has significantly impacted public transportation demand, with notable differences based on station characteristics. Station vitality is particularly crucial in Japan, where rail operators also generate revenue from nearby commercial activities. The size of the station, its city location, the type of travelers it serves, and its association with the city's functional areas all significantly affect the pandemic's impact and long-term recovery. Utilizing mobile spatial statistics (MSS), this research analyzes pandemic dynamics, providing a more accurate and comprehensive understanding of station vitality. By leveraging advanced analytical techniques and comprehensive data sources, this research aims to develop effective frequency planning strategies, enabling PT operators to better navigate future crises and ensure the resilience and sustainability of their services.

Keywords: Demand loss and recovery; Station Vitality; Railway station; Long-term forecast; COVID; Resilience Framework

Acknowledgements

After completing my journey of more than three years in Japan for my PhD, I would like to express my heartfelt gratitude to all the people along the way, who have helped me in various ways in a faraway foreign country.

Most of all, I would like to thank my supervisor, Prof. Jan-Dirk Schmöcker, who has guided my academic work and helped me in every way. Life is not always surrounded by happiness, but more than once during my time in Japan I have thought how grateful I am to have had you as my supervisor for what could have been the last part of my life as a student. It was under your guidance that I had the confidence to go through with it. You taught me how to determine my research direction, how to find interesting and meaningful topics, how to communicate with teachers and fellows and peers, how to write research papers, how to care for my juniors, and most importantly, you taught me a meticulous attitude towards research. You tolerated everything I did and always had a smile on your face. No matter how many years later, I will never regret pursuing my PhD in this laboratory, which was one of the best choices in my life.

I would also like to thank Prof. Yamada, Prof. Fujii, and Prof. Qureshi of Kyoto University, who were the committee members of my Ph.D. dissertation, and who gave me insightful comments in seminars and discussions. I would also like to thank the current faculty members of the Intelligent Transportation Systems Laboratory, Prof. Yamada and Prof. Schmöcker, as well as Dr. Nakao and Ms. Nishikawa, the secretary of the laboratory, who have helped me a lot in research and other aspects.

Thank you to the past and present students of our lab. Dr. Wenzhe Sun (now Prof. Sun) was the first member of the laboratory that I met, thank you for your help in my academic journey, and I wish you the best of luck and a bright future in your new world. Mr. Nishigaki, I would like to thank you for your help during my enrollment and wish you all the best in your work. I apologize for not being able to include all the names of my fellow researchers here. Studying abroad is a very good time, I hope we can all cherish it and see you again in the world once we leave here.

I would like to express my sincere gratitude to the Spring Program of Kyoto University for the financial support in the past three years, which has greatly helped me. I would also like to thank the AI DA

Program and DAAD-Kyoto Program for their financial support, which allowed me to go to the Technical University of Munich, Germany for a limited period of time for exchanges. Of course, I would also like to thank Professor Antoniou and Dr. Qinglong Lu for their care, especially Qinglong, I hope your career is also going well.

Finally, I would like to thank my parents Yingtao Dai and Ping Liu. It was your unwavering support at all times that enabled me to gather courage and face the unknown. Thank you for bringing me to this world and being able to feel the excitement along the way.

Preface

Parts of this dissertation have been published in journals, presented in conferences or else submitted for review are as follows

Journal papers

I. **Dai, J.**, Schmöcker, J.-D., & Sun, W. (2024). Analyzing demand reduction and recovery of major rail stations in Japan during COVID-19 using mobile spatial statistics. *Asian Transport Studies* (available online). **(Chapter 4 and Chapter 5)**

Under review/ To be submitted

II. **Dai, J.**, Sun, W., Lu, Q., Schmöcker, J.-D., & Antoniou, C. (2024). The resilience patterns of railway station vitality in response to COVID-19: A case study of Japan. *Cities*. **(Chapter 5 and Chapter 6)**

III. **Lu, Q.**, Dai, J., Sun, W., Schmöcker, J.-D., & Antoniou, C. (2024). Framework for evaluating urban resilience to pandemics: analysis of transport-related containment policies. **(Chapter 3)**

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Chapter 1 Introduction

1.1 Background

The COVID-19 pandemic has caused an unprecedented crisis in public transportation (PT) systems worldwide, there is an urgent need for a method to comprehensively evaluate and anticipate changes in passenger demand. The pandemic led to a drastic reduction in ridership due to lockdowns, social distancing measures, and the shift to remote work and online learning. This decline has significantly affected the operational viability of PT services and disrupted the broader urban mobility framework. In Japan, where rail stations are essential for daily commuting and economic activity, the impact has been particularly severe. Stations have multiple attributes such as commerce and tourism in addition to passenger distribution, and the surrounding land is mostly operated by railway companies. Therefore, a basic conclusion for operators is that the popularity value of a station is a barometer of passenger flow, and the higher the station's vitality value, the higher the station's demand will be.

Concerns about virus transmission have decreased public confidence in PT systems, prompting many to seek alternative modes of travel, such as private cars, bicycles, or walking. PT operators have implemented stringent hygiene and safety measures, including regular disinfection of vehicles and stations, increasing operational costs. The reduction in ridership has led to substantial fare revenue losses, putting financial strain on PT operators. Budget deficits have resulted in service reductions and delays in planned infrastructure projects. The broader economic downturn has exacerbated these challenges, as governments and PT operators struggle to balance budgets while ensuring the continuity of essential services.

Public transportation is crucial for providing mobility to those without private vehicles, including low-income populations, the elderly, and people with disabilities. The pandemic has disrupted this accessibility, making it harder for vulnerable groups to reach essential services such as healthcare, education, and employment. Reductions in service frequency and temporary route closures have disproportionately affected these communities, highlighting the need for inclusive recovery strategies.

PT systems have had to adapt quickly to changing circumstances, implementing new policies and procedures to ensure passenger and staff safety. These adaptations include modifying schedules to reduce crowding, introducing contactless payment systems, and enhancing communication with passengers. These changes have required significant logistical and financial resources, further straining already limited budgets.

The shift away from public transportation towards private vehicles has potential long-term environmental implications. Increased car usage can lead to higher emissions and congestion, undermining efforts to promote sustainable urban mobility. The pandemic has thus highlighted the need for resilient PT systems that can support environmental goals even during crises.

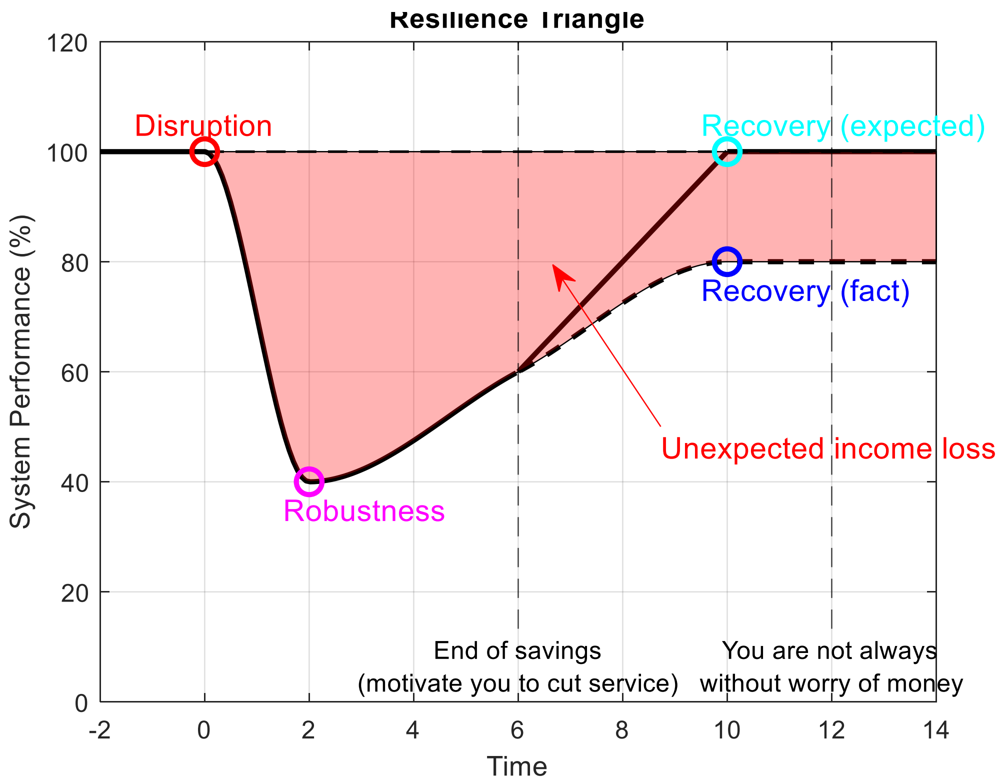

Figure 1.1 The resilience triangle illustrating system performance decline and recovery during a disruption

In the context of system resilience, the concept of the 'Resilience Triangle' is introduced as a framework to evaluate the performance and recovery of public transportation systems during disruptions, such as the COVID-19 pandemic. The 'Resilience Triangle', as shown in Fig. 1.1, illustrates the decline in system performance due to a disruption, the subsequent recovery process, and the associated performance loss over time. The area within the triangle represents the total impact of the disruption, including unexpected income loss due to reduced ridership and operational challenges. Understanding this dynamic is crucial for developing strategies that not only restore system performance but also enhance resilience to future shocks.

The recovery phase for public transportation has been marked by efforts to restore ridership and financial stability while ensuring public health. Enhanced hygiene measures, such as regular disinfection of PT vehicles and stations, installation of hand sanitizers, and mandatory mask policies, have been introduced to reassure passengers and reduce the risk of virus transmission. Service adjustments have been made to manage fluctuating demand and promote social distancing, balancing operational efficiency with passenger safety.

Financial support from governments has been crucial in covering revenue shortfalls and supporting essential services. Subsidies, grants, and loans have been provided to maintain service continuity and invest in necessary infrastructure improvements. The adoption of digital technologies, such as contactless payment systems, real-time passenger information apps, and data-driven demand forecasting tools, has been accelerated, enhancing operational efficiency and improving passenger experience.

Effective communication strategies have been essential in rebuilding public trust in PT systems. Transparent communication about safety measures, service changes, and pandemic-related updates helps reassure passengers and encourage the return to public transportation.

Understanding the patterns of change in station vitality during and after the pandemic is crucial for developing effective strategies to restore and enhance PT services. This includes analyzing how different factors, such as demographic shifts, changes in travel behavior, and economic conditions, influence station usage. By gaining insights into these patterns, PT operators can better adapt to ongoing challenges and future emergencies.

This leads us to explore the data sources used to quantify the impact of COVID-19 on public transportation operators, which will be discussed in the next section.

1.2 Objectives

This research aims to address the significant challenges faced by public transportation systems, particularly major Japanese rail stations, during and after the COVID-19 pandemic. The research focuses on two primary objectives, leveraging innovative approaches and methodologies to provide comprehensive insights and practical solutions:

1) Understand the different patterns of changes in station vitality and the factors influencing them during a pandemic:

The first objective is to comprehensively analyze station usage data to understand the different patterns of changes in station vitality during the pandemic and identify the factors influencing these changes. This involves selecting a diverse set of major Japanese rail stations to capture variations in location, size, and passenger demographics. A robust dataset, including ridership data, demographic information, economic indicators, and geographic factors, will be utilized.

Advanced analytical techniques, such as clustering algorithms and spatial analysis, will be employed to identify distinct patterns of change in station vitality. By integrating innovative data selection techniques and analyzing various factors, including demographic shifts, travel behavior changes, economic conditions, and public health measures, the research aims to provide a holistic understanding of how external influences impact PT usage during crises and recovery phases. This understanding will enable policymakers and PT operators to develop targeted interventions to mitigate the impacts of future crises and enhance the resilience of public transportation systems.

And, as part of this, the goal is to answer the following research questions:

- How the travel patterns at major rail stations have changed during the COVID-19 pandemic
- Determine the factors most influential in affecting station vitality during the pandemic
- How different demographic and economic conditions impact the recovery of station vitality
- The effectiveness of clustering algorithms and spatial analysis in identifying patterns of change
- Identify key predictors of station vitality recovery in the post-pandemic period

2) Forecasting long-term demand and balancing the trade-offs between service quality and operational constraints:

The second objective is to help PT operators make informed decisions about balancing service quality and operational constraints to maintain long-term demand. This involves assessing various long-term forecasting methods to determine their effectiveness during pandemics. Techniques such as time series analysis, machine learning algorithms, and hybrid models will be evaluated for their ability to capture the complex dynamics of PT usage during and after a pandemic. Plans for long-term adjustments will be developed, considering the magnitude and timing of changes, as well as constraints and interactions. These plans will address challenges such as fluctuating demand, financial uncertainty, and evolving passenger preferences. By providing PT operators with actionable insights into forecasting accuracy and adjustment plans, the research aims to help them adapt their operations effectively. The goal is to ensure that operators can balance the need to maintain service quality, which stabilizes long-term demand, with the necessity to manage operational costs during and after the pandemic.

And through this analysis answer in particular the following research questions:

➢ Explore the relationship between public health measures or policies and changes in station usage
➢ Identify the most effective methods for forecasting long-term demand during and after a pandemic
➢ Assess the role of resilience frameworks in informing PT operational decisions
➢ Explore how PT operators can balance the trade-offs between maintaining service quality and managing operational constraints
➢ Develop adjustment plans that PT operators can implement to stabilize long-term demand while controlling costs during and after the pandemic
➢ Determine the impact of different service quality levels on future passenger demand

By achieving these objectives, this research aims to offer practical insights and solutions that will assist policymakers, PT operators, and researchers in understanding and addressing the challenges posed by the COVID-19 pandemic.

1.3 Research outline

The outline of the remaining chapters is as follows:

After the introduction in Chapter 1, Chapter 2 delves into existing research on the COVID-19 pandemic's impact on public transportation. It explores various data sources used to quantify these impacts and reviews methodologies for long-term demand forecasting. This chapter identifies gaps in the current understanding of station vitality and sets the foundation for the research objectives.

Chapter 3 presents a framework for assessing the resilience of public transportation systems during pandemics. Using urban resilience theories and the 4R theory (robustness, redundancy, resourcefulness, and rapidity), the chapter evaluates transport-related containment policies during COVID-19. The Governance-Transport-Mobility-Resilience (GTMR) framework is applied to analyze the effectiveness of these policies. This framework will be used to guide subsequent data analyses and forecasts in Chapters 4, 5, and 6, and how operators should respond to a pandemic in Chapter 7.

In Chapter 4, based on the 4R theory in the resilience framework, we delineate the zones where station vitality goes from peak to trough and then back to stability, focusing on analyzing changes in station vitality during the short and medium term. Utilizing mobile phone mesh data, the chapter employs clustering techniques to identify patterns in station usage. The analysis aims to capture the dynamics of station vitality and understand the factors influencing these changes during the pandemic.

In Chapter 5, the research shifts to a detailed examination of the factors impacting station vitality through multinomial regression analysis. Based on the indicators in the existing framework, this chapter investigates the role of land-use factors, point of interest (POI) density, and other variables in predicting demand loss. The insights gained will help PT operators develop targeted interventions to mitigate the impact of future crises.

Chapter 6 explores long-term forecasting methods to predict post-pandemic public transportation usage. The chapter evaluates the effectiveness of ARIMAX (Autoregressive Integrated Moving Average with Exogenous variables) and LSTM (Long Short-Term Memory) models in capturing complex demand dynamics. The aim is to provide PT operators with robust forecasting tools to optimize service frequencies and resource allocation. Among the exogenous variables, the proportion of the affected population derived from the policy layer (top layer) of the resilience framework and the number of new cases were selected.

Chapter 7 addresses the crucial trade-off between maintaining service quality and managing operational constraints during the COVID-19 pandemic. The chapter develops a theoretical model that balances the costs and benefits of different service levels. It discusses how high service quality can stabilize long-term demand but incurs higher costs, while lower service quality reduces costs but may lead to a decline in future demand. This analysis aims to guide PT operators in making informed decisions that ensure both cost efficiency and demand retention.

Finally, Chapter 8 provides the conclusions of this research, including a summary of key findings, contributions to the field, and future research directions.

The structure of this research is outlined in Fig. 1.2. This figure illustrates the logical flow of the thesis, starting with the background and literature review, moving through data collection and analysis, and culminating in the development of a theoretical model and its application through a case study. It also serves as a roadmap for the reader, providing a visual summary of the research process. Each chapter builds on the previous one, ensuring a cohesive and comprehensive exploration of the impact of COVID-19 on public transportation systems, particularly focusing on major Japanese railway stations.

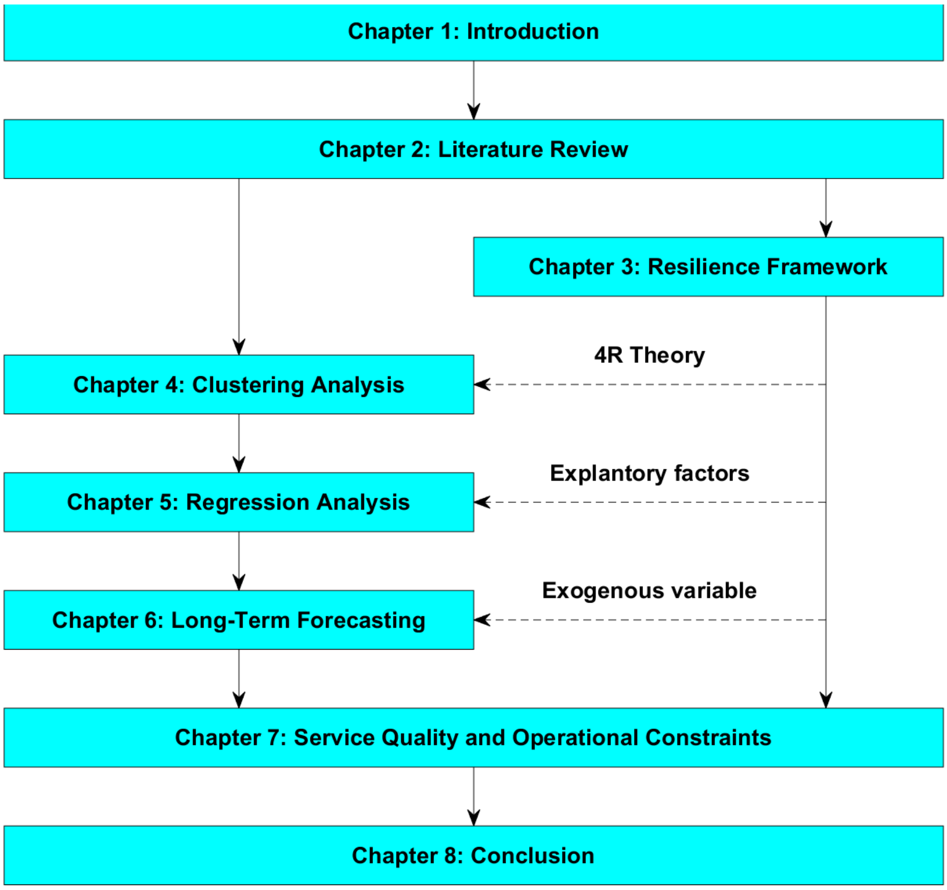

Figure 1.2 Research outline

Chapter 2 Literature review

This chapter explores existing research on the impacts of the COVID-19 pandemic on public transportation, focusing on several key areas. First, it examines the various data sources used to quantify these impacts, such as smart card data, cell phone data, and public transportation ridership data. Traditional data collection methods can be challenging during a pandemic due to issues like data cleansing. However, data collected automatically by mobile device operators can mitigate these problems, although it is crucial to consider the content and limitations of the data itself. Next, the chapter discusses the specific effects of the pandemic on public transportation, including the loss of passengers, layoffs of employees, and the financial instability of operators. For example, research has shown that ridership drops dramatically in major cities during pandemics, but the impact on different modes of transportation, such as subways and buses, may vary. The initial assumption is that the pandemic causes people to cancel trips and stay home, leading to fewer passengers, especially in crowded areas like stations, which makes them ideal for studying these impacts. Additionally, the chapter addresses the uncertainty of post-pandemic travel behavior. Once restrictions are lifted, it is unclear whether people will resume traveling as much as they did before the pandemic. This uncertainty underscores the importance of summarizing methods for long-term demand forecasting and understanding how different studies have approached the challenge of predicting public transport demand during a crisis.

We highlight the need for an integrated approach to assessing the impact of pandemics on public transport systems by examining both global and regional studies. This comprehensive review sets the stage for developing the framework presented in the next chapter.

2.1 Global impact of COVID-19 on public transportation and tourism

Like many catastrophic events, the COVID-19 pandemic has wrought significant damage across various industries. Particularly hard-hit are sectors such as public health, tourism, and public transportation (Gaskin et al., 2021; McCartney, 2021). Research by Ganguly et al. (2020) further underscores that nations with a heavy reliance on tourism saw more pronounced declines in GDP during the COVID-19 crisis.

The global impact of the COVID-19 pandemic, with severe restrictions in many countries and a sharp decline in the use of public transport, has been costly as discussed in a wide range of literature (Liu et al., 2020; Wielechowski et al., 2020; Hasselwander et al., 2021; Borkowski et al., 2021; Habib et al., 2021; Safitri et al., 2022). In addition, travel patterns are gradually changing in the wake of the pandemic, and with the recovery of demand (Beck et al., 2020; Tashiro et al., 2020; Gudmundsson et al., 2021; Wang et al., 2022), a “new normal” has emerged in many countries (Haarlem et al., 2022; Ha et al., 2023; Östh et al., 2023; Dantsuji et al., 2023). In some cases, likely irreversible changes in travel patterns and changes in commuters are affecting the subsequent operational strategies of public transport agencies (Zhou et al., 2021; Bert et al., 2021; Hu et al., 2021; Shimamoto et al., 2023). Recent discussions also argue that repeated states of emergency may not be effective in controlling the spread of COVID-19 (Liu et al., 2022), that movement restrictions may be effective for a short period of time but ineffective in reducing trips (Kim et al., 2021). Based on this, others conclude that the length of the policy lag and the magnitude of the impact on the transport system require more attention (Bian et al., 2021; Sun et al., 2023).

Japan, being a country heavily dependent on tourism, suffered extensively due to the pandemic. Economically, the repercussions of the COVID-19 pandemic have been particularly devastating for cities heavily reliant on tourism as a cornerstone of their economies. The imposition of widespread global embargoes and travel restrictions has precipitated economic stagnation, soaring unemployment rates, and a protracted path to recovery (Gössling et al., 2020; Hall et al., 2020; Schmöcker, 2021). According to the "COVID-19 Tourism Index" provided by Yang et al. (2021), as of October 2020, the global tourism industry was operating at only around one-third of its pre-pandemic capacity, translating into trillions of dollars in lost export revenue from international tourism. Bui et al. (2021) underscored the necessity of prioritizing domestic tourism initiatives as a primary strategy for bolstering resilience during the recovery phase, pending the return of international demand. However, despite the potential temporary upsurge in domestic tourism resulting from de-globalization trends (Prayag, 2020), the overall trajectory of the tourism sector remains downward (Niewiadomski, 2020), with projections indicating that tourism may be among the last industries to rebound fully (McCartney et al., 2021). Matei et al. (2021) suggested recovery timelines ranging from one year to 18 months. Given its inherent dependence on human interaction, the tourism sector faces significant challenges in cultivating resilience through traditional means of innovation and adaptability (Gupta and Sahu, 2021). Consequently, strategies aimed at curbing tourist numbers while enhancing the quality of the tourist experience (and subsequent spending) have emerged as imperative measures for the sector's sustained viability.

Japan consistently has one of the highest public transport ridership rates in the world, meaning that the potential impact of a COVID-like crisis would be greater (Schouten et al., 2024). The impact was uneven across different segments of the network (Shimamoto et al., 2023). The importance of city size has been studied before, with data showing that metropolitan areas are suffering more (Ribeiro et al., 2020; Armstrong et al., 2020; Chang et al., 2021). During the pandemic, intra- and inter-city public transport is kept to a minimum, which means that the type of travelers and travel OD are restricted, often with strong characteristics (Chowdhury et al., 2022; Tan et al., 2021). Further, clearly the number of COVID-19 cases as well as government restrictions can significantly affect the travel demand of travelers (Sun et al., 2020; de Paiva et al., 2021). Arimura et al. (2020), using time-series data, discussed that it led to a redistribution of population density. Rasca et al. (2021) suggest that population density plays a key role to understand the differences in public transport decline during the pandemic. Their data suggests that during COVID-19, the decrease in public transport patronage is strongly related to the regional infection rate, with the virus spreading significantly faster in cities with strong hubs (Bao et al., 2022). Others have shown that the number of pandemic-related cases and deaths are increasing the closer to the airport (Gaskin et al., 2021; Wang et al., 2021). However, the specific role of transport hubs in these effects has not been discussed in detail in these studies.

2.2 Data sources and targets to quantify COVID impacts on operators

Numerous studies have analyzed the impact of the COVID-19 pandemic on transit demand worldwide, showing a severe reduction in public transportation usage due to stringent restrictions adopted by many countries. Data obtained from smart cards can provide insights into how travelers adjusted their travel patterns. For instance, Halvorsen et al. (2021) quantified the dramatic demand loss in New York using such data. Similarly, an analysis by Siewwuttanagul et al. (2023) in Bangkok found that ridership levels decreased significantly, with the metro experiencing larger declines. Comparable impacts have been reported from the UK, Hong Kong, and Seoul (Vickerman et al., 2021; Zhang et al., 2021; Ku et al., 2021).

In addition to smart card data, cell phone data obtained from operators and other sources have received attention from researchers for quantifying COVID-19 impacts (Östh et al., 2023; Alessandretti, 2022; Liu and Yamamoto, 2022). This data provides a comprehensive and accurate picture of movements, including user attributes and origins-destinations (OD) information, rather than just the station where people board and alight. Smart card data and cell phone data can complement each other in the analysis of COVID impacts. For instance, Hara et al. (2021) used cell phone data to estimate Japan-wide indicators of behavioral change, finding a significant decrease in travel and cross-province travel with a slow recovery.

Focusing on the COVID impacts on stations is crucial as these are important economic hubs for many cities. The busyness of a railway station reflects the communication between this place and other areas as well as the prosperity of the city itself. The vitality of the city is closely related to the proximity to the station (Yang et al., 2021). In Japan, many shops at stations are owned by rail operators, so the reduction in travel leads to multiple economic losses.

Ridership is the most obvious characteristic of change, but current ridership clustering studies are limited by issues such as data availability, making temporal impact comparisons difficult (Yan et al., 2021; Gupta et al., 2021; Roman et al., 2022). Other studies have used online surveys (Harantová et al., 2023), daily county vehicle miles traveled (VMT) (Fisher et al., 2023), and other parameters to aid the analysis. The impacts of the pandemic will clearly differ between stations. When categorizing different stations, it is common practice to consider the absolute number of travelers present (Lu et al., 2024). However, quantifying the impact of a pandemic is more informative when considering the amount or percentage reduction in travelers. Furthermore, distinguishing types of travelers is important for understanding the total economic impact. Commuters might purchase some small products, but certain goods sold at a station are mostly bought by tourists and other longer-distance travelers. Therefore, mobile statistics are suggested as a good alternative to measure impact.

Obtaining indicators of the demand impact alone is insufficient to derive policy implications. It is necessary to explore the reasons behind these indicators. Station characteristics, related to the size and economic situation of the city, can be used as explanatory variables. At the “macro-level,” factors such as city size, economic status, and network location can be considered (Zhou et al., 2021). For example, Cao et al. (2020) found that the location balance of JR (Japan Railway) is better compared to private railways in the Tokyo metropolitan area, contributing to resilience. Similarly, countries with high-speed rail networks exhibit polycentric characteristics, which can also contribute to resilience (Yang et al., 2018).

At a more "micro-level," it is necessary to consider the characteristics of the stations themselves, including the shops present and the Points of Interest (POI) in its vicinity. Niu et al. (2023) found that transport facilities, businesses, and population density are the main influences on the choice of station location, and these factors also influence the nature and extent of passenger congestion at different stations (Lu et al., 2024; Ma et al., 2023). External factors, such as improving service quality and reducing fares during periods of low ridership, should not be ignored as they can motivate people to travel (Taylor et al., 2003; Zhu et al., 2023; Lu et al., 2024).

Understanding the multifunctionality of stations, including shopping, leisure, entertainment, and office activities, is also important. Smart card data can only capture information about traveling, but not other activities at the station. Mobile phone data can capture the time that visitors (and station staff) spend at the station, providing a comprehensive view of "station vitality." Station vitality encompasses a variety of factors such as commercial activity, accessibility, and overall functionality in addition to passenger flow. Vongvanich et al. (2023) used "Google Popular Times" to analyze trends in station "popularity," but the lack of absolute values was a major drawback. The mobile phone data used in this research provides information on the changing trends of users within the station, in addition to the personal attributes of the users, offering a breadth and depth that is beneficial for analysis (Yamaguchi et al., 2023; Wu et al., 2023).

2.3 Urban resilience and long-term demand forecast under COVID-19

The COVID-19 pandemic has had a profound impact on healthcare systems worldwide, particularly exposing vulnerabilities in weaker health infrastructures. Surprisingly, even more developed health systems in Europe and North America faced significant challenges in responding effectively to the crisis (Rathnayake et al., 2021). Health systems globally have had to navigate a delicate balance between pandemic response measures and ongoing healthcare needs, necessitating innovative strategies such as reverse triage or the establishment of alternative healthcare facilities (Lam et al., 2006). For instance, the construction of temporary hospitals to augment bed capacity has proven instrumental in both containing the epidemic's spread and relieving pressure on strained healthcare services (Roosa et al., 2020). However, reduced transport accessibility can hinder access to medical facilities, exacerbating the situation (Dingil and Esztergár-Kiss, 2021). This underscores the interdependence between the health system and transportation infrastructure, emphasizing the importance of integrated strategies and close coordination between these sectors (K. L. Chen et al., 2021). Collaborative efforts can include the dissemination of real-time epidemic and transport information through shared channels to enhance infection prevention awareness, manage travel demand, and mitigate health risks (Cochran, 2020; Darsena et al., 2020).

While the definition of urban resilience may vary across different domains, it consistently revolves around two primary measurements: absorption capability and recovery capability. Moreover, considerable attention has been devoted to identifying the factors associated with these two measurements during pandemics.

The absorption capability, a crucial aspect of urban resilience during pandemics, encompasses various factors. Previous experiences with epidemics play a significant role in this regard (Malhotra and Venkatesh, 2009). For instance, cities that faced the SARS outbreak drew upon their crisis recovery plans, implementing similar strategies to combat COVID-19 outbreaks swiftly. Lessons learned from SARS emphasized the importance of prompt quarantines and the adoption of sanitary and personal protective measures (Chien and Law, 2003). Additionally, factors such as land use and city size are pertinent. While higher urban density is often deemed sustainable for conserving land resources and reducing per capita carbon emissions (Y. Chen and Zhang, 2020; Egidi et al., 2020), it presents challenges during pandemics. Larger cities may struggle to contain the spread of diseases due to increased population movement and economic activity (Bui et al., 2021). However, the completeness of health care infrastructure and advanced urban governance capability in these cities can counter such negative factors and improve the timeliness of pandemic control and thus resistance to COVID-19 (J. Chen et al., 2021). To bolster urban resilience in pandemic emergency management, early and proactive measures, such as allocating resources toward healthcare, are imperative in urban resource management.

In addition to managing the immediate aftermath of a disaster, resilience is also gauged by the capacity to recover to a state that is, at minimum, equivalent to pre-disaster conditions. Amidst challenging economic circumstances, research has increasingly focused on COVID-19 exit and recovery strategies (Jamal and Budke, 2020; McCartney, 2021), with emerging technologies poised to play a pivotal role in the recovery phase (Gretzel et al., 2020; Hall et al., 2017). Leveraging big data analytics and information and communication technologies (ICTs), population movements are being monitored more rigorously during the COVID-19 pandemic than ever before (Haraguchi et al., 2022; Mahajan et al., 2021; Peak et al., 2020; Wilder-Smith and Freedman, 2020). This enhanced monitoring facilitates the implementation of effective intervention policies, such as travel bans and quarantines (Bauch and Anand, 2020; Chinazzi et al., 2020; Lancet, 2020a, 2020b). Given the significant alterations in urban life induced by the pandemic, scholars have suggested that COVID-19 may prompt a reevaluation of existing practices, particularly in hard-hit sectors like tourism (Carr, 2020; Sigala, 2020). Notably, Ritchie and Jiang (2019) advocate for a focus on building resilience in future research endeavors. Considering the potential for future outbreaks, there is an urgent imperative for disaster response and post-disaster recovery planning. This necessitates collaboration among stakeholders across various industries and the systematic development of proactive pandemic response strategies by cities. Accordingly, in Section 3, we present an implementation framework that outlines the process from disaster impact mapping to decision-making, aiming to facilitate comprehensive and effective responses to pandemics.

The existing literature has convincingly quantified how much public transport demand is affected during certain waves of the COVID-19 pandemic, and studies using smartcard or public transport passenger data are common (Jenelius et al., 2020; Almlöf et al., 2023). However, it is more temporal and short-term, and the long-term is not yet well understood. In order to better understand the demand resilience patterns of different stations, we also need to forecast long-term demand.

In time series forecasting studies, ARIMA and SARIMA are very common methods, and many researchers have used these methods in their studies (Atabay et al., 2022; Milenković et al., 2018; Chuwang et al., 2022). However, COVID-19 does not have a clear time period and the frequency, lengths and strengths of the waves are varying (Kolozsvári et al., 2021). ARIMAX can be used to include external factors, such as station characteristics (Su et al., 2020). Jiao et al. (2021) have also used ARIMAX models to predict daily bus ridership. However, there are limitations, for example, most station characteristics are fixed (e.g. land use, POIs, etc.) and hence cannot be used to predict relative changes for that station unless the “general importance” of such a POI for demand trends is understood. Therefore, many researchers have focused on the field of deep learning, and LSTM methods are one of the most widely used approaches, as it is very effective in dealing with continuous values (Hochreiter et al., 1997). Halyal et al. (2022) analysed the traffic situation in developing countries using the LSTM method and showed more satisfactory results than using SARIMA. For understanding and forecasting the impact of an event like COVID-19, however, no single method may be able to fully summarize its characteristics (Ghalehkhondabi et al., 2019; Jiao et al., 2019).

2.4 Conclusion

In summary, existing literature has well quantified that public transportation demand is indeed heavily affected by COVID-19, but most studies take the city or country as a whole and do not pay much attention to the characteristics of the station itself. Station vitality is, however, important especially in Japan where many rail operators are generating revenues also from stores, restaurants and hotels in and near the station buildings. The size of the station, the location of the city in which it is located, the type of travelers it carries, and its association with the functional area of the city are likely to impact the pandemic’s impact including long-term recovery. Considering the limitations of smart card data in quantifying station vitality, we base our analysis on mobile spatial statistics (MSS). Such data have been widely used previously for analysis and early warning of population movements during disasters (Arimura et al., 2020; Wu et al., 2021; Hashimoto et al., 2022). Further, Tatsu et al. (2017) analyzed the impact of the opening of the Shinkansen on the number of tourists in Kanazawa and Toyama cities using MSS data and found an increase in the total number of tourists around the stations as well as out-of-town tourists along the railroad line. This suggests that total changes in the number of travelers and people visiting the stations can be captured more accurately and completely with our data.

This research will use this data to analyze the dynamics during the COVID-19 pandemic in terms of number of people in mesh areas. We select meshes where major stations are located to obtain the change in the number of persons staying in the station area including travelers, based on which the station characteristics can be explored more deeply. Since the mesh area covers all the people in the station, station staff, shoppers as well as local and long-distance travelers using the same station are counted, which is different from smart card data and analysis with other payment data that usually focuses on urban travel.

Next, we will present a comprehensive framework for evaluating and responding to the impacts of such pandemics on public transportation systems. This framework will guide the analysis in subsequent chapters, providing ideas for possible solutions.

Chapter 3 Urban resilience framework and public transport operator implications

3.1 Introduction

The increasing occurrence of both natural and man-made disasters has driven a surge in the development of urban resilience evaluation frameworks. These frameworks are essential for informed decision-making when urban systems face disruptions. They encompass various dimensions, methodologies, and types of disasters, offering a comprehensive approach to understanding and enhancing urban resilience. In the context of the COVID-19 pandemic, public transportation (PT) systems have been significantly impacted, necessitating a specific focus on PT resilience within the broader scope of urban resilience.

Urban resilience evaluation frameworks are designed to support decision-making by assessing how well urban systems can absorb, recover, and adapt to disruptions. These frameworks are categorized based on dimensions they consider, types of disasters they address, and whether they utilize qualitative or quantitative methodologies. Table 3.1 provides a detailed comparison of various urban resilience evaluation frameworks, highlighting their key characteristics and supporting decision-making. By categorizing these frameworks based on dimensions, types of disasters, and methodologies, Table 3.1 helps in identifying the most suitable framework for specific urban resilience assessments. The table illustrates the diversity in approaches and the need for a multifaceted understanding of urban resilience to effectively address different types of disruptions.

Urban resilience can be conceptually divided into five overarching dimensions: institutional, physical, social, economic, and natural. Each dimension encompasses a range of factors critical for assessing the overall resilience of urban systems. For instance, terms such as "physical," "built infrastructure," "built environment," and "infrastructural" are synonymous and represent the physical dimension. Similarly, "natural," "ecological," and "environmental" describe the natural dimension, while "institutional," "policy," "governance," and "organizational" denote the institutional dimension. Table 3.2 details the components and indicators used to measure these dimensions, compiled from sources like Ribeiro and Pena Jardim Gonçalves (2019) and Datola (2023). This table provides a structured approach to assessing urban resilience, detailing components and indicators for the five key dimensions, thereby aiding in evaluating the overall resilience of urban systems. The indicators in Table 3.2 offer a comprehensive view of the factors influencing resilience, underscoring the importance of a holistic approach to urban resilience that considers physical infrastructure, social systems, governance, economic stability, and natural environments.

Table 3.1 Urban resilience evaluation frameworks

Publication	**Dimensions**	**Disasters**	**Resilience properties**	**Type**
Ribeiro and Pena Jardim Gonçalves (2019)	Physical, natural, economic, institutional, social	Natural, climate	Redundancy, diversity, efficiency, robustness, connectivity, adaptation, resources, independence, innovation, inclusion, integration	Qualitative
Zuniga-Teran et al. (2020)	Policy, built infrastructure, natural, social	General	Robustness, redundancy, resourcefulness, rapidity	Qualitative
Datola (2023)	Physical, natural, economic, institutional, social	General	Robustness, redundancy, diversity, integration, resourcefulness, inclusivity, reflectiveness, flexibility, transparency	Qualitative
Zhao et al. (2022)	Built environment, metabolic flow, governance, social	General		Quantitative
Xun and Yuan (2020)	Ecological, economic development, social development	Natural, climate		Quantitative
Liu et al. (2021)	Economic, social, infrastructural, environmental	Natural		Quantitative

B. Wang et al. (2022)	Economic, social, infrastructural, ecological	General	Quantitative
Feng et al. (2020)	Ecological	General	Quantitative
Xu et al. (2021)	Economic, environmental, governance, technological, built infrastructure	Flooding	Quantitative
Rezvani et al. (2022)	Environmental, economic, organizational, social, technical	Constructed asset	Quantitative
Ruan et al. (2021)	Ecological, economic, social	Flooding	Quantitative

Table 3.2 Components and indicators of the five dimensions of urban resilience (largely based on Liu et al. (2021), Zhao et al. (2022), and Wang et al. (2022))

Dimensions	**Components**	**Indicators**
Institutional	Governance, organized governmental services, warning and evacuation, emergency response, disaster recovery	II_1: Household registered population II_2: Proportion of population joining basic pension insurance for employeesII_3: Fiscal expenditure II_4: Maintenance and construction funds II_5: Proportion of employees of enterprises, institutions and government in population II_6: Unit density of hospitals and health centers II_7: Number of doctors
Physical	Physical infrastructure, land use, transport, housing, structural design	PI_1: Road surface area PI_2: Number of public vehicles PI_3: Total inventory turnover rate

		PI_4: Communication network coverage
		PI_5: Area covered by public hazard maps
		PI_6: Length of drainage pipes
		PI_7: Density of water supply pipelines in built-up area
		PI_8: Density of sewers in built-up area
		PI_9: Total size of emergency shelter area
		PI_{10}: Population of internet users
Social	Human capital, lifestyle and community competence, community capital, social and cultural capital, demographic behavior, risk Knowledge, vulnerable people	SI_1: Per capita disposable income
		SI_2: Living area of urban residents
		SI_3: Population density
		SI_4: Proportion of expenditure for social security and employment in fiscal expenditure
		SI_5: Registered unemployment rate
		SI_6: Engel coefficient
		SI_7: Number of college students
Economic	Economic development, employment level, business sectors	EI_1: GDP per capita
		EI_2: GDP growth rate
		EI_3: Proportion of tertiary industry in GDP
		EI_4: Dependence on foreign trade
		EI_5: Proportion of fiscal revenue in GDP
		EI_6: Per capita disposable income of urban residents
		EI_7: Scientific research fund intensity
Natural	Ecosystems, waste and water	NI_1: Green-covered area
		NI_2: Area of public green land
		NI_3: Annual average emission of SO_2
		NI_4: Water consumption
		NI_5: Air quality excellent days ratio
		NI_6: Ratio of wastewater centralized treated

Existing urban resilience frameworks can be broadly categorized into qualitative and quantitative approaches. Qualitative frameworks typically establish connections between the dimensions of urban resilience and resilience properties, elucidating how aspects like institutional resilience contribute to the robustness of the urban system. However, these frameworks often lack the granularity needed to analyze the dedicated impact of individual components. For instance, Datola (2023) and Ribeiro and Pena Jardim Gonçalves (2019) discuss how qualitative frameworks connect resilience properties with urban resilience dimensions but note their limitations in quantifying specific impacts.

Quantitative frameworks, on the other hand, decompose dimensions into urban components/subsystems and define performance indicators for each, enabling the quantification of urban resilience through an index system. Methods such as the Entropy weighting model, deviation maximization, and factor analysis are used to calculate indicator weights. For example, Zhao et al. (2022) and Wang et al. (2022) utilized the Entropy weighting model, while Xun and Yuan (2020) applied deviation maximization, and Liu et al. (2021) employed factor analysis to determine the weights of indicators.

These quantitative methods allow for a more detailed and data-driven approach to assessing urban resilience. However, they also have limitations, such as potential biases due to endogeneity among performance indicators of subsystems and a primary focus on long-term resilience with limited attention to short-term response actions (Liu et al., 2021; Zhao et al., 2022).

Urban resilience frameworks are further distinguished by their focus on general disaster scenarios versus specific types of disasters. General frameworks provide broad insights into urban resilience at a macroscopic level, while disaster-specific frameworks focus on the functions and effects of subsystems in response to particular disasters. For instance, general frameworks often analyze the potential damage caused by natural disasters, which can limit their applicability to other types of emergencies (Xu et al., 2021; Rezvani et al., 2022).

In the context of public transportation, the COVID-19 pandemic has exposed significant vulnerabilities, highlighting the need for a tailored resilience framework. This chapter introduces a comprehensive framework to assess and enhance the resilience of PT systems during pandemics, drawing upon established urban resilience theories and adapting them to the specific context of PT resilience. The framework incorporates key dimensions of urban resilience, including robustness, redundancy, resourcefulness, and rapidity (4R theory), and addresses the unique challenges posed by the COVID-19 pandemic.

By integrating the principles of urban resilience with the specific needs of PT systems, the proposed framework aims to enhance the capacity of PT systems to withstand and recover from pandemic-induced disruptions. This approach not only supports the immediate response to crises but also promotes long-term sustainability and resilience of urban transportation infrastructures.

3.2 Application of urban resilience against pandemics to PT resilience

Evaluating the effectiveness of transport-related containment policies is crucial for understanding how these measures influence system resilience during a pandemic. Using the Governance-Transport-Mobility-Resilience (GTMR) framework, we analyze how these policies impact urban resilience, focusing on their implications for public transportation systems affected by COVID-19. In this section, we will expound upon the effectiveness of transport-related containment policies from the perspective of system resilience. The GTMR framework is then applied to interpret how these policies influence urban resilience.

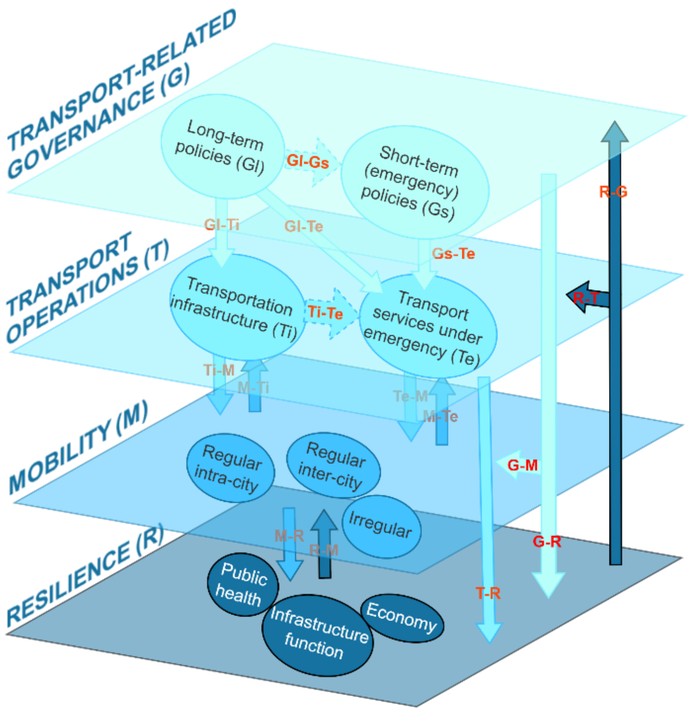

Figure 3.1 GTMR framework for urban resilience against pandemics

Selected transport-related containment policies have been instrumental during the COVID-19 pandemic. Table 3.3 presents 15 commonly adopted transport-related emergency response policies (S1 – S15) utilized in combating the COVID-19 pandemic. In the framework outlined in Fig. 3.1, these policies correspond to the effects manifested in Gs-Te, Te-M, and partially T-R components. The potential impacts of these policies are summarized into five distinct groups (E1 – E5), as depicted at the bottom of the table.

Table 3.3 Emergency response strategies for the COVID-19 pandemic and their effects

ID	Strategy	Effect
S1	Cancellation of international passenger flights	E1
S2	Reduction of intercity buses, trains, high-speed trains, planes, etc.	E1
S3	Cancellation of intra-city public transport operation	E2
S4	Publishing infection risk warnings, appeal citizens not to make non-essential trips	E2, E5
S5	Posting trajectories of the infected	E3, E5
S6	Daily disinfection of public transport vehicles	E4
S7	Wearing a mask and maintaining social distancing in public transport vehicles	E4
S8	Scale management of taxis	E2
S9	Stay-at-home orders	E2, E3
S10	Ride-sharing companies laid off management staff and froze driver sign-ups	E2
S11	Using taxis to provide point-to-point goods delivery to residents	E2, E3
S12	Offering free usage of city bicycles	E3
S13	Back-door-only loading policy	E3, E4
S14	Opening specific lanes to bicycle users	E3
S15	Improving the public transport information system	E3, E5
Effect category		
E1	Reducing connections to other cities	
E2	Reducing intra-city mobility	
E3	Managing crowdedness	
E4	Improving health and safety management system of public transport	
E5	Improving the update, release and forecast of public information	

Specifically, policies S1 and S2 are aimed at reducing the number and capacity of available transportation options, thereby weakening the connections of the target city to other places (E1). Others, such as S3, S8, and S10, seek to minimize intra-city mobility (E2) by either reducing supply or demand. These measures focus on limiting human mobility to curb transmission. Conversely, a third group of policies aims to manage public crowding (E3) by increasing awareness of precautions (S5, S15), reducing the need for public outings (S9, S11), and minimizing physical contact in public transportation (S12, S13, S14). Policies like S13, S6, and S7 primarily aim to create a healthy and safe public transport environment (E4). Additionally, policies focused on enhancing the dissemination and forecasting of public information (E5), such as S4, S5, and S15, play a crucial role during the pandemic outbreak. Considering long-term strategies, we designate corresponding policies with similar effects as S(E1), S(E2), S(E3), S(E4), and S(E5), respectively. In the framework outlined in Fig. 3.1, these long-term policies are responsible for interactions Gl-Gs, Gl-Ti, Gl-Te, Ti-M, and partially T-R.

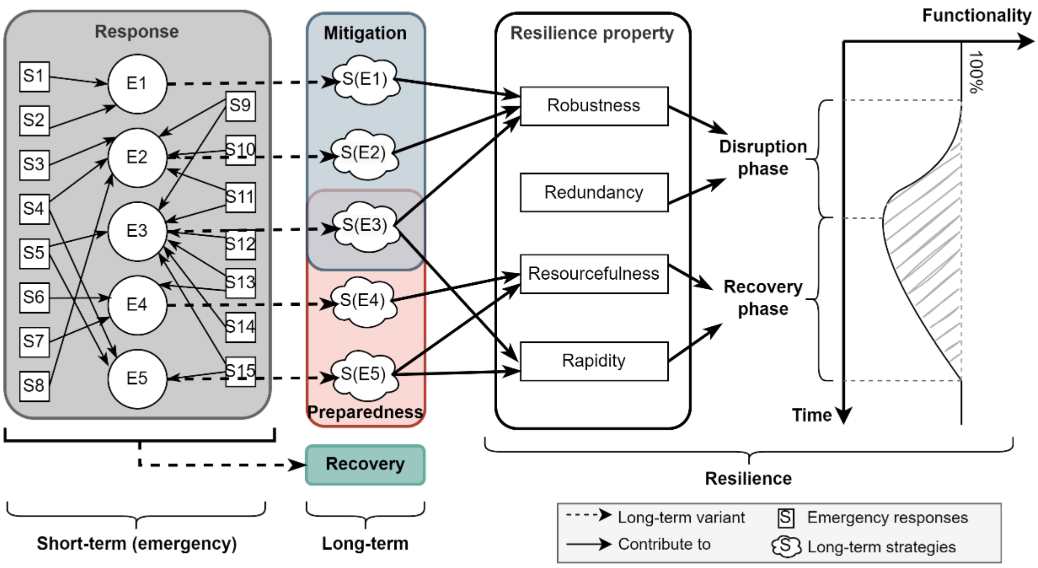

Figure 3.2 Policies categorization and contribution to resilience properties

Faturechi and Miller-Hooks (2015) delineate four distinct stages in disaster management based on the disaster life cycle: mitigation, preparedness, response, and recovery. Mitigation, preparedness, and recovery strategies are considered long-term, while emergency responses are short-term. Mitigation strategies aim to diminish the likelihood of a disaster occurring or limit its consequences. Preparedness strategies are crafted to ensure swift and effective responses post-disaster. Response strategies entail short-term adaptive measures implemented to restore system functionality. Recovery strategies can be seen as an extension of emergency responses. All policies listed in Table 3.3 fall under response strategies. Their long-term counterparts, designated as S(E1) – S(E5), may be categorized as mitigation, preparedness, and/or recovery strategies based on their effects, as elaborated in Fig. 3.2. Furthermore, we will demonstrate how these strategies enhance resilience properties (i.e., robustness, redundancy, resourcefulness, and rapidity) as defined in the "4R framework" detailed by Bruneau et al. (2003).

In Fig. 3.2, we illustrate how these strategies bolster system resilience by linking strategy groups to stages of the disaster life cycle and associating them with resilience properties. It is worth noting that long-term strategies addressing E1 and E2, i.e., S(E1) and S(E2), serve as mitigation strategies aimed at enhancing the system's robustness. While E3, E4, and E5 represent valid goals for both short- and long-term strategies, the long-term counterparts of E1 and E2 could be termed "reducing dependency on other cities" and "minimizing the need for intra-city mobility", respectively. Consequently, S(E1) aims to foster a self-sufficient industrial structure and a more autonomous city, while S(E2) strives to mitigate significant spatial and functional heterogeneity in land use. S(E3) can be classified as either mitigation or preparedness strategies since routine crowdedness management can mitigate the likelihood of large-scale transmission early in outbreaks (mitigation), while experience and developed techniques can expedite response times (preparedness). These strategies contribute to the system's robustness and rapidity. S(E4) and S(E5) are geared towards developing a responsive public health management system and an advanced information dissemination system, making them preparedness strategies that enhance the system's resourcefulness. Additionally, S(E5) can also bolster rapidity. However, it is essential to note that none of the strategies directly contribute to the redundancy property. In the context of pandemics, redundancy could entail ensuring sufficient professional staffing at critical positions, enabling the system to function effectively even when some personnel are quarantined. It is pertinent to mention that all strategies listed in Table 3.3 can be extended and adjusted until the end of the pandemic, effectively transitioning into recovery strategies.

By definition, the system's performance during a disturbance can be divided into disruption and recovery phases. As outlined by Zhou et al. (2019), the disruption phase assesses the system's ability to maintain functionality, focusing primarily on robustness and redundancy. In contrast, the recovery phase evaluates the system's capacity to restore functionality, primarily influenced by resourcefulness and rapidity. Resilience loss is then quantified as the integral of the difference between the pre-disaster normal functionality and the actual functionality throughout the entire disaster period. It is important to note that all short-term strategies are implemented to expedite recovery from the disruption phase. However, for the sake of clarity, this aspect is not depicted in Fig. 3.2.

As an illustrative example, we employ the GTMR framework to analyze the strategies delineated in Table 3.3. Fig. 3.3 highlights five distinct strategy groups (SGs) categorized according to the effect categories outlined in the table. In the ensuing discussion, we primarily focus on transport services under emergency, which signify the immediate impact of policies. Specifically, we delve into their effects on public transport services, with a particular emphasis on five key aspects: service frequency, provision of real-time information, operating hours, pricing adjustments, and vehicle cleanliness.

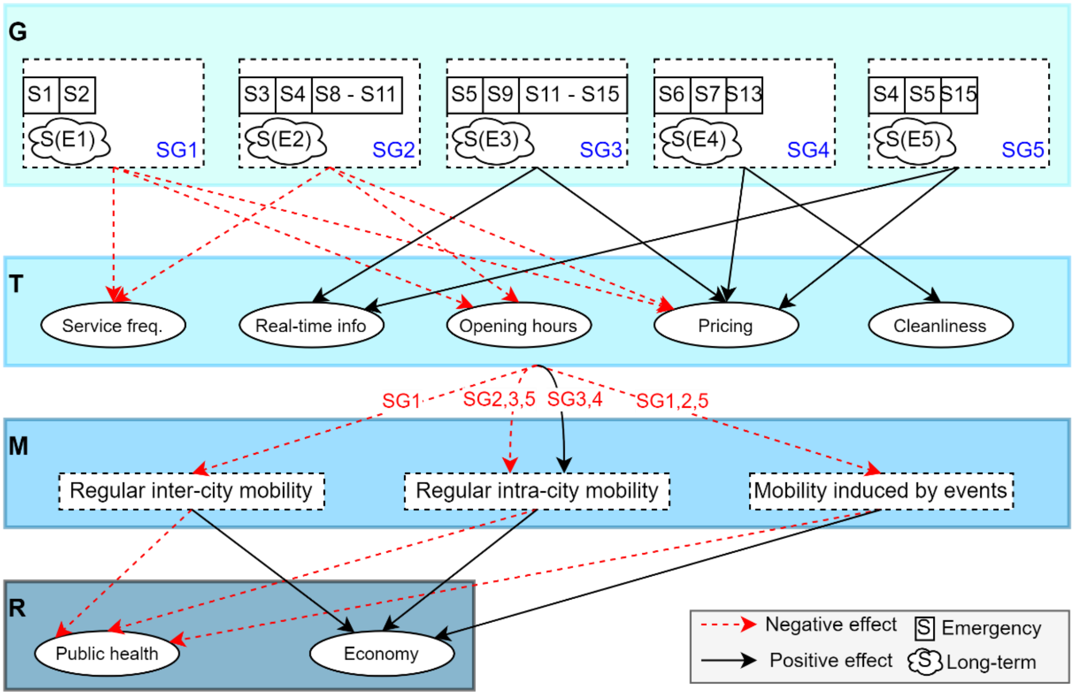

Figure 3.3 Applying the GTMR framework for urban resilience in COVID-19

Indeed, SG1 is primarily geared towards diminishing connectivity with other cities. This strategic approach entails a notable reduction in the availability and frequency of transportation services to and from other urban centers. Given the dynamic nature of the strategies involved, challenges may arise in various other facets, including pricing considerations. For instance, in response to dwindling passenger demand, airlines might opt to hike ticket prices to safeguard their profitability. Furthermore, a noticeable decline in both inter-city and event-induced mobility is anticipated under these circumstances. This suggests that SG1 holds the potential to curtail the importation of cases and bolster local epidemic control efforts, rendering strategies within SG1 typically viable at the outset of a local epidemic or during periods of rapid escalation in infected cases. It is imperative to note that the implementation of SG1 necessitates robust local control measures to maximize efficacy.

SG2 is geared towards minimizing physical contact by curtailing intra-city travel demand. Specifically, S3 entails a reduction in service frequency and availability, necessitating service rescheduling and potential fare adjustments. Similarly, S8 and S10, crucial measures for the survival of taxi and transport network companies (TNCs) amid economic downturns, are expected to result in reduced traffic volume. Moreover, S11 underscores the interchangeability of various transportation modes. Analogous to SG1, SG2 is anticipated to have adverse effects on “availability”, “frequency”, and “ticketing”. Implementation of SG2 is expected to lead to decreased intra-city and event-induced mobility.

SG3 targets the reduction of public crowding. Strategies like S5, S9, and S11 achieve this by curbing intra-city mobility demand, while S12 and S14 promote cycling for short-distance trips. Consequently, the strategies within SG3 exhibit conflicting effects on mobility demand. However, the promotion of cycling usage can mitigate the infection risk associated with public transportation while still facilitating intra-city mobility. Furthermore, S15 furnishes operators with information regarding demand fluctuations, aiding in the development of an appropriate fare structure.

SG4 focuses on enhancing the safety of public transportation by ensuring vehicles are clean and hygienic. When public transport is perceived as safer and more reliable, there may be an increase in intra-city travel demand. However, the requirement to wear masks and maintain social distancing within vehicles (S7) may deter some passengers from using public transport due to physical discomfort or personal preference. Therefore, S7 has a mixed impact on mobility demand.

The reduction in inter-city, intra-city, and event-induced mobility can help mitigate the spread of COVID-19. However, these measures aimed at restricting mobility can also have adverse effects on the economy. Therefore, it is essential to consider both the effectiveness of pandemic control measures and the economic losses incurred when evaluating urban resilience to pandemics such as COVID-19.

3.3 Discussion on impact of service reduction

Service reduction, a common response to the decline in ridership during the COVID-19 pandemic, has significant implications for PT resilience. Evaluating the effectiveness of transport-related containment policies through the GTMR framework provides insights into how these reductions impact urban resilience, particularly in terms of robustness, resourcefulness, and rapidity.

Reducing services can lead to multiple potential outcomes, influenced by the interplay of different strategies within the GTMR framework. Policies aimed at reducing inter-city and intra-city connectivity (S1, S2, S3, S8, S10) weaken the ties of a city to other areas (E1) and minimize intra-city mobility (E2). While these measures can help control the spread of the virus by limiting movement, they also pose risks of economic isolation and a decline in commercial activities around transit hubs. This can lead to prolonged economic stagnation and reduced accessibility if not managed well.

The demand sensitivity to service reduction varies. Special offers like fare reductions, similar to Germany's "9 Euro Ticket," can stimulate demand by making PT more affordable, particularly for price-sensitive users. Enhancing passenger confidence through rigorous hygiene measures and clear communication about safety protocols can also help recover demand. Passengers are more likely to return to PT if they perceive it as safe, convenient, and cost-effective.

However, service reductions must consider several limitations. Timing is critical; reducing services during peak hours can severely affect commuters. Essential needs must be met, ensuring that critical services remain accessible. Operational requirements must balance cost savings with maintaining infrastructure and equipment, avoiding long-term damage.

Strategies like S5, S9, S11, S12, and S14 aim to reduce public crowding and promote alternative modes of transport such as cycling. These measures can maintain mobility while enhancing safety, though they require substantial infrastructure investment and public acceptance. By promoting cycling and other alternatives, these strategies contribute to robustness and rapidity by providing alternative travel options.

Policies aimed at ensuring clean and hygienic public transport (S6, S7, S13) can improve public confidence and potentially increase ridership. Enhanced safety measures contribute to resourcefulness by maintaining a safe travel environment, but they also incur additional costs and operational challenges. Long-term strategies (S(E4), S(E5)) focus on developing responsive public health management systems and advanced information dissemination, enhancing the system's resourcefulness and rapidity.

The outcomes of service reduction, therefore, depend on the implementation and effectiveness of these strategies. Prolonged reduction in services, particularly inter-city connectivity, can lead to economic isolation. If cities fail to adapt by developing self-sufficient structures, the economic impact could be severe, leading to long-term stagnation and reduced economic resilience. Effective long-term strategies that mitigate intra-city mobility and enhance spatial balance could lead to more sustainable urban development. This outcome requires coordinated efforts to ensure accessibility and mobility are maintained, particularly for vulnerable groups. Investments in safety and hygiene can rebuild public trust and increase ridership. If paired with robust health management systems and effective communication, this can lead to a resilient PT system capable of quickly recovering from disruptions.

Promoting alternative modes of transport such as cycling can reduce dependence on public transport, providing a buffer during service reductions. This requires significant investment in infrastructure and public buy-in but can enhance overall urban mobility and resilience.

In conclusion, service reductions necessitated by the COVID-19 pandemic must be strategically managed to balance immediate needs with long-term resilience. The GTMR framework provides a structured approach to understanding these impacts and guiding adaptive strategies. By focusing on robustness, resourcefulness, and rapidity, PT operators can mitigate the adverse effects of service reductions and support the recovery of urban mobility. Understanding these impacts through the GTMR framework provides valuable insights into balancing immediate needs with long-term resilience, ensuring public transportation systems remain robust, flexible, and capable of recovering from future disruptions. With this foundational framework in place, the next chapter will focus on short- and medium-term demand change analysis using station clustering techniques, providing detailed data analysis on station usage patterns during the pandemic.

Chapter 4 Station clustering and short and medium-term demand change analysis

After obtaining a comprehensive framework for resilience analysis, we need to know the impacted conditions in a real situation in order to decide what decisions to use to intervene. In this chapter, we utilize mobile spatial mesh data to examine changes in station vitality during the COVID-19 pandemic. We present comprehensive vitality data for all stations in a time-space format, filtering out the most severely impacted periods and including timeframes before and after the pandemic to capture the entry and exit phases. By selecting weekly average vitality data as the clustering object, we identify several typical patterns of change at major Japanese stations during the pandemic and explore the factors influencing these changes. For instance, some stations experienced a significant drop in demand followed by a swift recovery, while others continued to face declining ridership. This chapter delves into the specific paths of change at different stations within the context of the pandemic, providing detailed analyses of various scenarios. Understanding these patterns is crucial as it allows us to identify and categorize stations based on their responses to the pandemic, setting the groundwork for the regression analysis of influencing factors that will be conducted in the next chapter. By examining these detailed paths of change, we can better understand the dynamics of station vitality and the underlying reasons for differing recovery rates.

4.1 The mobile phone mesh data

4.1.1 MSS data and station vitality

The mobile spatial statistics (MSS) used in this research are created based on the Nippon telegraph and telephone corporation (NTT) DOCOMO mobile network mechanism (Masayuki et al., 2013). MSS uses operational data from the mobile terminal network for population estimation and estimates coverage in essentially the same way as the mobile terminal service area. MSS provides data by gender, age, and county (or municipal) residence under standard grids (e.g., 1km and 500m grids) for hourly or longer time intervals. For data privacy and security considerations, age, gender information and residence information are, however, not linked. For our purposes, we primarily used information on place of residence, which will be discussed later.

Its data production process consists of three processes: non-identification, aggregation, and hiding (Ichiro et al., 2013), and mainly consists of privacy of identity information, number of devices by area, and deletion of less populated areas. It is hence important to understand that the MSS information reflects the number of mobile devices that appear in the standard grid at a given time. For example, if a device stays in a grid for 10 min (1 in 6 h), then the final result reflected in the system for that device is 1/6, and so on.

Figure 4.1 Station areas (painted in red) fit or exceed a standard 500m grid (red lines). Hakata station (left) and Tokyo station (right) as example

The MSS is fed by information from about 80 million devices. Since the total population of Japan in 2021 is counted at 126 million, this accounts to a high market share. Differences to the total population are corrected by NTT DOCOMO according to their share in each region and among age groups (Masayuki et al., 2013). The only situation that requires attention is the potential variation in behavior between different subscriber groups of different cell phone operators. However, for a basic need such as travel, such differences are unlikely to occur and therefore the estimation accuracy of the MSS data can be considered sufficiently accurate (Hara et al., 2021). In this research, we use 500m x 500m mesh data considering the usual building size of train stations (one mesh grid). Some large stations, such as Shinjuku and Tokyo, extend beyond one grid. At these stations in particular the platforms are longer than 500m, as shown in Fig. 4.1. However, considering the usually short time travelers spend on platforms and the increase in non-station space that may result from increasing the number of grids, we stick to using one grid per station and choose the one that covers the main part of the station building.

Our research process begins with the selection of suitable stations based on characteristics, and after data preparation a cluster analysis of the amount of change in transit demand during COVID-19 and an attempt to explain the intrinsic reasons, as shown in Fig. 4.2.

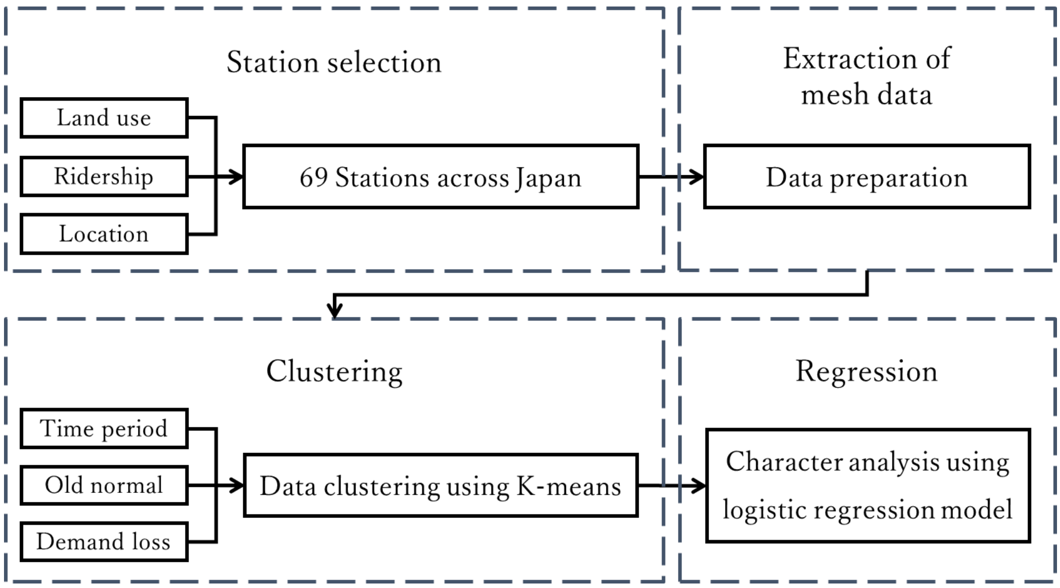

Figure 4.2 Station clustering research process

4.1.2 Target station selection

The selection of stations for transit demand loss analysis depends on the research question, the scope of the research, and the availability of data. To obtain an understanding on the differences across Japan we choose major stations that are, generally, well-connected and heavily used. Table 4.1 lists factors considered in our data analysis.

Further to the selection rules, given our research objective, we chose at least one station from each of the 47 prefectures of Japan. The resulting 69 stations selected according to the above principles of importance and geographical diversity are shown in Table 4.2. For ease of understanding and graphing, we numbered the stations in the order of the mesh area code from largest to smallest, along with their station name abbreviations in capital letters.

To illustrate the locations of the 69 stations, we have mapped them in Fig. 4.3, using the station name abbreviations introduced in Table 4.1. Locations of the same color in the map represent the same area: from top to bottom, Tohoku-Hokkaido area (light green), Kanto area (green), Shin-Etsu area (pink), Chubu area (orange), Kansai area (blue), Chugoku area (light orange), Shikoku area (light blue) and Kyushu area (red).

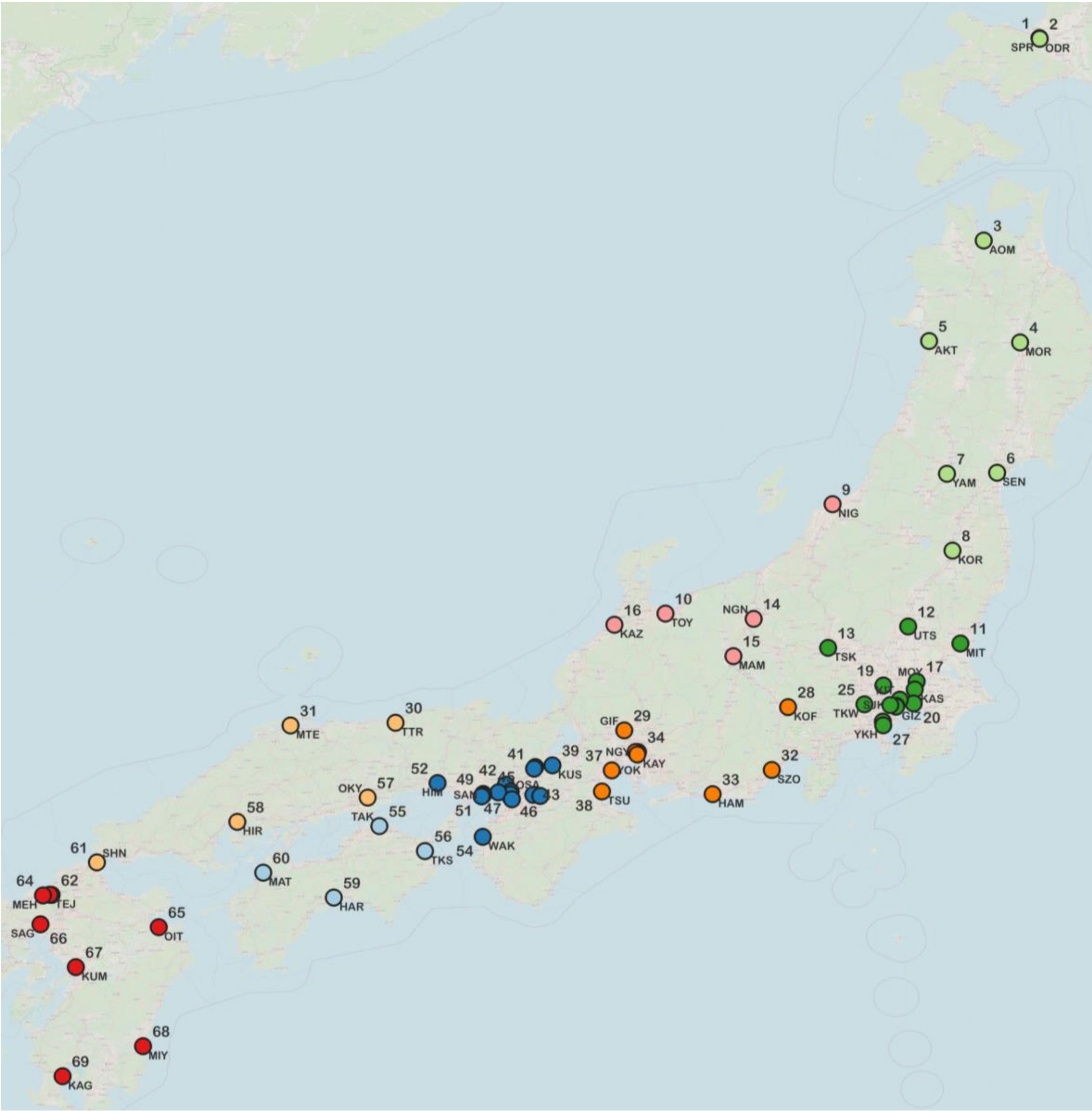

Figure 4.3 Location of the selected stations

Table 4.1 Station selection considerations

Factor	Consideration
Location	Stations located in central areas of the city or near major transportation hubs are more likely to have higher demand and greater sensitivity to changes in transit services.
Ridership	Stations with higher ridership are more likely to be affected by changes in transit services, and therefore more suitable for demand loss analysis
Transit network	Stations that are part of a larger transit network or serve as important transfer points are more likely to be suitable for analysis, as they are more likely to have a broader impact on travel patterns
Availability of data	The availability of data on transit demand, such as ridership data, mobile phone data, or other relevant data sources, can also influence station selection

Table 4.2 Stations information

Sta No.	Station	Abbr.	Sta No.	Station	Abbr.
1	Sapporo	SPR	36	Kanayama	KAY
2	Odori	ODR	37	Kintetsu-Yokkaichi	YOK
3	Aomori	AOM	38	Tsu	TSU
4	Morioka	MOR	39	Kusatsu	KUS
5	Akita	AKT	40	Gion-Shijo	GIO
6	Sendai	SEN	41	Kyoto	KYT
7	Yamagata	YAM	42	Ishibashi handai-mae	HAN
8	Koriyama	KOR	43	Gakuemmae	GAK
9	Niigata	NIG	44	Kintetsu-Nara	NAR
10	Toyama	TOY	45	Shin-Osaka	OSN
11	Mito	MIT	46	Namba	NAM
12	Utsunomiya	UTS	47	Osaka	OSA
13	Takasaki	TSK	48	Koshien	KSE
14	Nagano	NGN	49	Shin-Kobe	SKB
15	Matsumoto	MAM	50	Sannomiya	SAN

16	Kanazawa	KAZ	51	Kobe	UKB
17	Moriya	MOY	52	Himeji	HIM
18	Kashiwa	KAS	53	Tennoji	TNJ
19	Omiya	OMI	54	Wakayama	WAK
20	Nishifunabashi	NIF	55	Takamatsu	TAK
21	Kitasenju	KIT	56	Tokushima	TKS
22	Tokyo	TYO	57	Okayama	OKY
23	Ginza	GIZ	58	Hiroshima	HIR
24	Shinjuku	SJK	59	Harimayabashi	HAR
25	Tachikawa	TKW	60	Matsuyama City	MAT
26	Shin-Yokohama	YKN	61	Shimonoseki	SHN
27	Yokohama	YKH	62	Hakata	FUK
28	Kofu	KOF	63	Tenjin	TEJ
29	Gifu	GIF	64	Meinohama	MEH
30	Tottori	TTR	65	Oita	OIT
31	Matsue	MTE	66	Saga	SAG
32	Shizuoka	SZO	67	Kumamoto	KUM
33	Matsumoto	HAM	68	Miyazaki	MIY
34	Sakae	SAK	69	Kagoshima-Chuo	KAG
35	Nagoya	NGY			

4.1.3 Data Correlation to Station Demand (with ridership)

The accuracy of MSS as an estimate for the number of people in a mesh can be considered to be good (Hara et al., 2021). However, in this research, its correlation with transit demand needs further examination as clearly not only traveling is a reason to visit the station mesh. Further, as noted, people who stay longer in the station mesh will be counted more than people who only stay briefly. We selected 20 stations with high passenger ridership in Table 4.2 in 2019 for the analysis, where station passenger ridership data is counted and updated annually by the Ministry of Land, Infrastructure, Transport and Tourism. (Note that we do not have more detailed monthly or weekly data from the Ministry). The data contains the average daily number of passengers boarding and alighting at all stations in operation in

Japan. The MSS data is then selected for a more typical week, with a time period of 6am to 11pm, the hours of operation for most stations.

As can be seen from the data in Table 4.3, the ratio between ridership data and MSS data is not constant because the two types of data are not collected in the same way and the stations themselves do not have the same attributes, but the correlation coefficient value between the two reaches 0.72, which implies that the MSS data is suitable for studying changes in transit demand. Moreover, we suggest that the "error" is also meaningful as it describes the degree to which the station is visited for non-travel purposes, such as shopping or eating at the restaurants in the station building or in its immediate vicinity. We take the ratio of 2019 and 2020 MSS data as the x-axis and ridership as the y-axis, as shown in Fig. 4.4, and most of the stations are in the region around 1.5. Of the eight stations that deviate significantly from the majority, the top one is No. 22, Tokyo Station, the leftmost is No. 3 Aomori Station (the northernmost point of the main island), and the six rightmost stations are all from Kyushu Island. This suggests that though ridership did significantly reduce in Kyushu, the impact on station vitality is not as significant. We suggest this is because stations are not as highly attractive for non-travel activities as some of the other stations in our database and travelers do not stay for long.

Table 4.3 Ridership and MSS mesh population in 2019

Station	Ridership	MSS	Ratio	Station	Ridership	MSS	Ratio
Shinjuku	3836469	704298	5.45	Sannomiya	682346	263275	2.59
Osaka	2357064	572609	4.12	Kyoto	675559	290831	2.32
Yokohama	2101709	458887	4.58	Kanayama	478556	159499	3.00
Tokyo	1339555	560795	2.39	Hakata	460926	370065	1.25
Kitasenju	1294209	148505	8.71	Shin-Osaka	449455	121931	3.69
Nagoya	1272809	415475	3.06	Tachikawa	413541	262590	1.57
Namba	830531	351535	2.36	Kashiwa	400105	222571	1.80
Tennoji	732512	244883	2.99	Sendai	387724	205596	1.89
Omiya	700854	318763	2.20	Sapporo	370484	277069	1.34
Nishifunabashi	693803	129573	5.35	Ginza	297002	510787	0.58
Correlation coefficient					0.723		

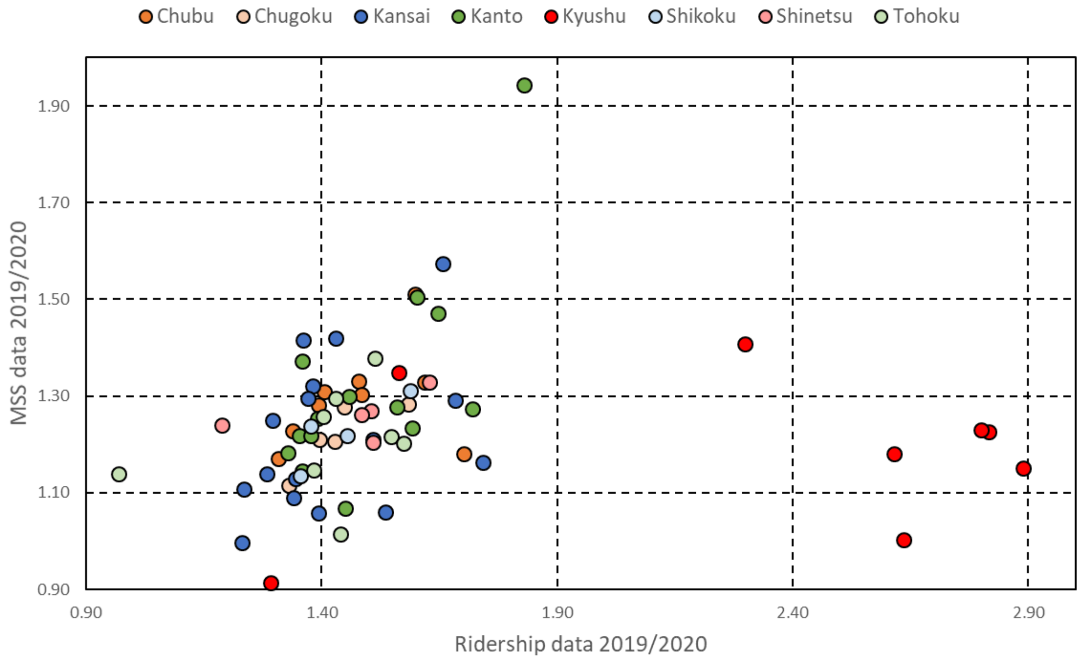

Figure 4.4 Ratio of ridership vs MSS data in 2019 and 2020 by station numbers

4.2 Clustering variables and results

4.2.1 Cluster time period (obvious resilience triangle) and the number of clusters

The focus of the subsequent analysis is the first COVID-19 pandemic. Fig. 4.5 shows the averages of MSS data for all 69 stations from October 2019 to October 2021 at 9 AM and 6 PM. As can be seen from the graph, the values in January 2020 were able to remain at a level comparable to that of 2019; however, after the first relatively significant drop in March 2020, there was a severe drop in April, and by May demand was down to 30% of the previous level, mainly due to the COVID-19 pandemic and the severe control measures implemented by the Japanese government at the same time. In June, when the controls were lifted, the values gradually rebounded, reaching the first post COVID-19 peak from early June to mid-July. Therefore, we targeted the time period from March 2020 to July 2020. Since the ridership characteristics are not the same for weekdays and holidays (loss of ridership on holidays is less than on weekdays), we only consider data for stations on weekdays.

We take the population at different stations during the same observation period as input for clustering to find groups of stations with similar patterns. Here we use the K-means algorithm, the most commonly used clustering algorithm, to obtain the results.

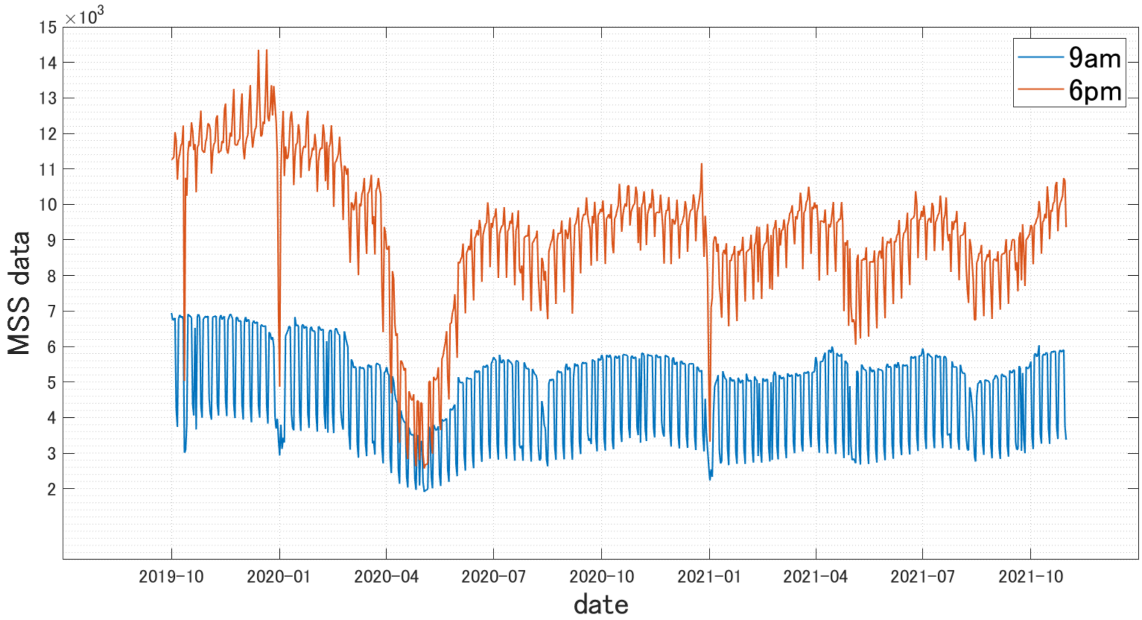

Figure 4.5 All stations time-series average at 9am and 6pm

Since the absolute population varies greatly among the stations, we focus on relative demand change. That is, for each station n the data during COVID-19 is divided by the average before COVID-19, as in Eq. (1).

$$\bar{x}_{nw} = x_{nw}^{c} / x_{n}^{b} \tag{4.1}$$

In Eq. 4.1, x_n^b is the average value of weekly workdays at each station n before COVID-19 (October 2019 to December 2019) and x_{nw}^c is the average value for week w during the first COVID-19 wave, that is, the 20 weeks from March 2020 to June 2020). Although most cities are negatively affected by the pandemic, there are a few exceptional cases, i.e., the range of values for $\bar{x}_{nw}$ may also be greater than 1.

The set of n stations $(x_1, x_2, \ldots, x_n)$, are divided into k sets $(k \leq n)$ such that the sum of squares within the group is minimized. That is, we find the clusters S_i that satisfy Eq. 4.2, where μ_i is the mean value of all points in S_i (Angela et al., 2022):

$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \|\bar{x}_{nw} - \mu_i\|^2 \tag{4.2}$$

Our research process begins with the selection of suitable stations based on characteristics, and after data preparation a cluster analysis of the amount of change in transit demand during COVID-19 and an attempt to explain the intrinsic reasons, as shown in Fig. 4.2.

Next, we need to determine the optimal number of clusters, and many methods have been provided in the past literature. We use the elbow method (an internal clustering validation method) in this research to cluster the dataset with a series of k-values of k-means and calculate the sum of squares of the distances between each point and its nearest center of mass, also known as the sum of squares of errors (SSE) and sum of squares within clusters (WCS).

As shown in Fig. 4.6, we start with $k = 2$ and keep increasing until $k = 12$. After reaching a certain value of k, the training cost (i.e., diminishing returns) decreases sharply and eventually reaches a stable level as the value of k increases further. $k = 2$ has the largest diminishing returns, slows down significantly after $k = 5$, and the rate of change becomes indistinguishable from $k = 7$. Thus, we conclude that $k = 5$ is the optimal number of clusters.

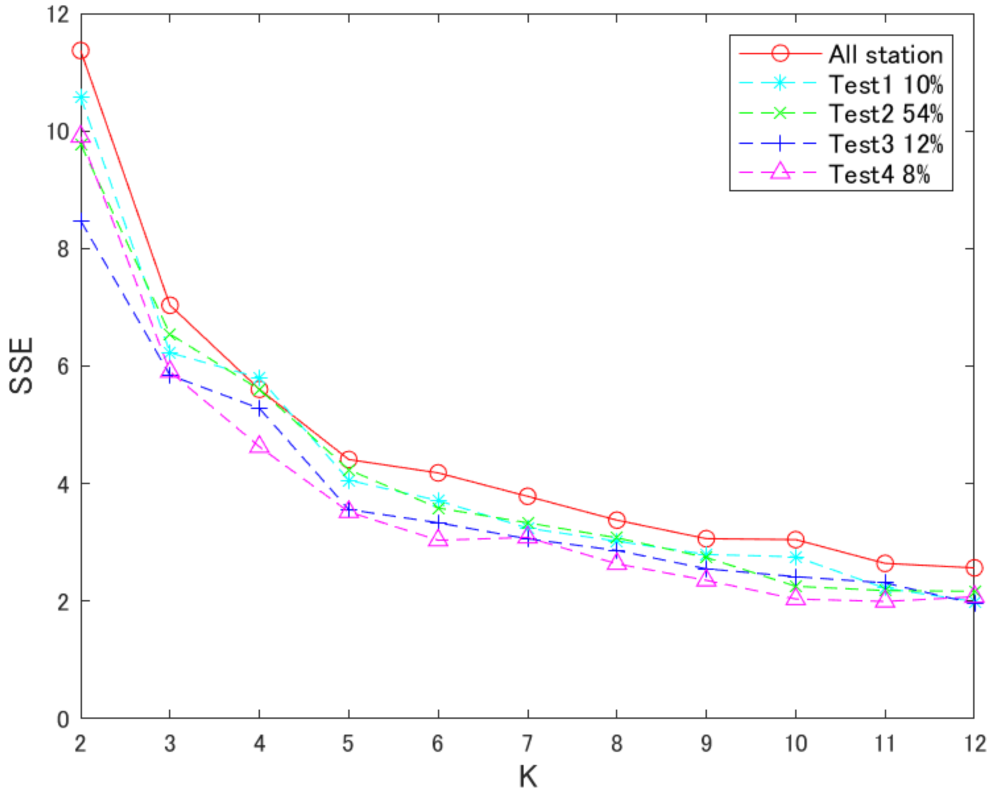

Figure 4.6 Choice of number of clusters and sensitive test

To test the stability of the clustering, we also performed a sensitivity analysis. Nine of the 69 stations were randomly removed, and the remaining stations were clustered and compared with the previous results. As can be seen in Fig. 4.6, the best k value for the four sensitivity tests remains 5 and the deviation of the clustering results is around 10% for three of the four tests, where deviation is measured in terms of number of stations being assigned to a different cluster. Only in one case is the deviation significant, with 54%. Nevertheless, accounting for the randomness present in the clustering results, we consider the results obtained to be within acceptable limits and consider our clustering as stable as also the following discussion will show.

4.2.2 Cluster results and features (location, ridership, population)

Fig. 4.7 shows the change in ridership for the 5 different clusters for the 20 consecutive weeks starting from March 2020. It can be seen that all clusters have different degrees of decline starting from week 4, reaching the lowest value in week 10, and then start to recover, reaching the first stable peak after the impact in week 18. In terms of transit demand analysis, we can say that the demand is steady when there is no significant change in ridership levels over a period of time. The length of time required for demand to be considered steady depends on the context and specific characteristics of the transit system being analyzed. In the current research, we combined the stabilization at weeks 16-20 and the small peak at week 18 to make a judgment. Cluster 5 was the most affected, with a 60% reduction in ridership, the lowest value was only about 20% of the pre-COVID-19 demand, and by week 19 it did not recover to 90% of the level of week 4. Cluster 4 shows a similar trend to Cluster 5, but with a “shift” of about +10% for all weeks. Cluster 3 and Cluster 2 were less affected, but still the demand dropped to 40% of the pre-COVID demand. A common feature, but different to Clusters 4 and 5 is that for both the demand recovered to the pre-COVID level by week 18; Cluster 1 was largely unaffected by the pandemic, with the lowest value being only 5% less. Further the stations in Cluster 1 recovered rapidly, on average even exceeding the pre-COVID level at week 14. We note that ridership gradually increases from Cluster 1 to Cluster 5 not only during the COVID period but also in the pre-COVID period. This can be interpreted as more travel demand and more diverse travel purposes worsen the impact.

In conclusion, the five clusters can hence be subdivided into three types: unaffected (e.g., cluster 1); affected but ridership can largely recover (e.g., clusters 2 and 3); and significantly affected and ridership fails to recover (e.g., clusters 4 and 5).

As we can see from the previous analysis, Cluster 1 has hardly been affected in terms of ridership, which appears surprising given the scale of the pandemic. There could be several reasons why some stations may not have been affected or even experienced an increase in transit demand during the COVID-19 pandemic. One possibility is that the station is located in a residential area where people are not dependent on public transit for their daily commute (as seen in the local rates). Another possibility is that the station is a transfer point for a critical transportation route that was not significantly impacted by the pandemic.

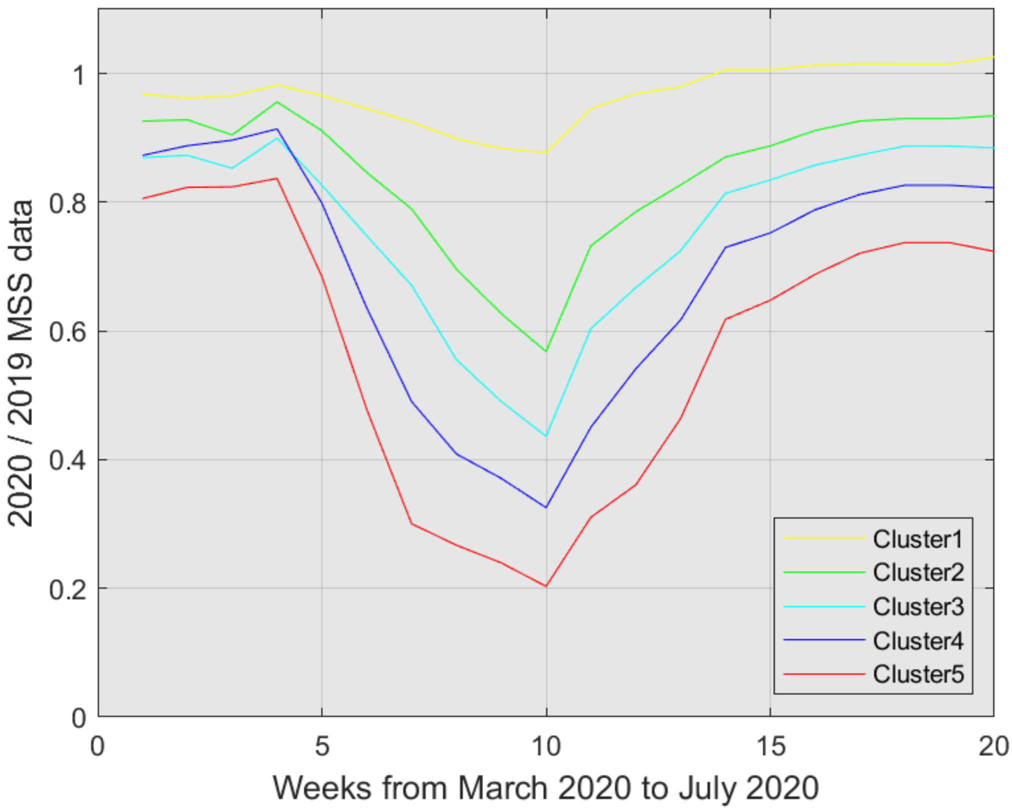

Figure 4.7 Ratio changes of the 5 clustering groups on the time series

Fig. 4.8 shows a map with the clusters illustrated by different colors. We labeled Clusters 1 through 5 as yellow, green, cyan, indigo, and red, respectively, with darker colors representing a greater degree of COVID-19 impact. The yellow Cluster 1 stations are usually distributed in remote areas and around big cities. Travelers mostly pass through and stay only for a short time at these stations as they do not offer extensive shopping and leisure facilities. This means that the weight of these travelers in the MSS data will be relatively low. Cluster 5, red stations, are all urban center stations in Japan's three major metropolitan areas (no exceptions), and usually these stations have commercial facilities attached to these in which travelers will stay longer. As hence travelers tend to stay longer at these stations, this means the impact in our MSS data is highlighted.

Cluster 3 and Cluster 4 are mainline stations in various regions of Japan. Cluster 4 stations are closer to major cities than Cluster 3 and are more affected. Instead, Cluster 2 stations are usually in more remote or longer commuting areas, with mainly local traffic or a large amount of stable traffic to major cities (e.g. satellite towns). With these observations we can depict the general characteristics of the stations in each cluster as shown in Table 4.4.

We close this section by noting that for Tokyo, Nagoya and Osaka we have more than one station in our dataset. As can be seen in Fig. 4.8, stations in the same city are not necessarily in the same cluster. We observe that the main JR station in each of these cities is in Cluster 5 due to the above discussed reasons. Other stations in each of these cities are often in different clusters as they fulfill different roles. Examples include Kitasenju Station in Tokyo, Sakae Station in Nagoya and Namba Station in Osaka (all subway stations). They are all in Cluster 3 or 4, probably because they cater more for intra-city travel including commuting, which is less impacted by COVID than inter-city travel.

Table 4.4 Characteristics of stations in each cluster

Cluster number	Distance to big cities	Description	Example
1	Very near or very far	Suburban stations or central stations in remote areas	Akita, Moriya
2	Near or far	Central cities or coastal cities with less traffic, satellite cities of large cities	Kagoshima, Kobe
3	Medium	Cities on major transportation routes	Sendai, Hiroshima, Kumamoto
4	Close	Areas with a high concentration of tourists, shopping centers	Hakata, Sapporo
5	No distance	Big cities	Tokyo, Nagoya, Osaka

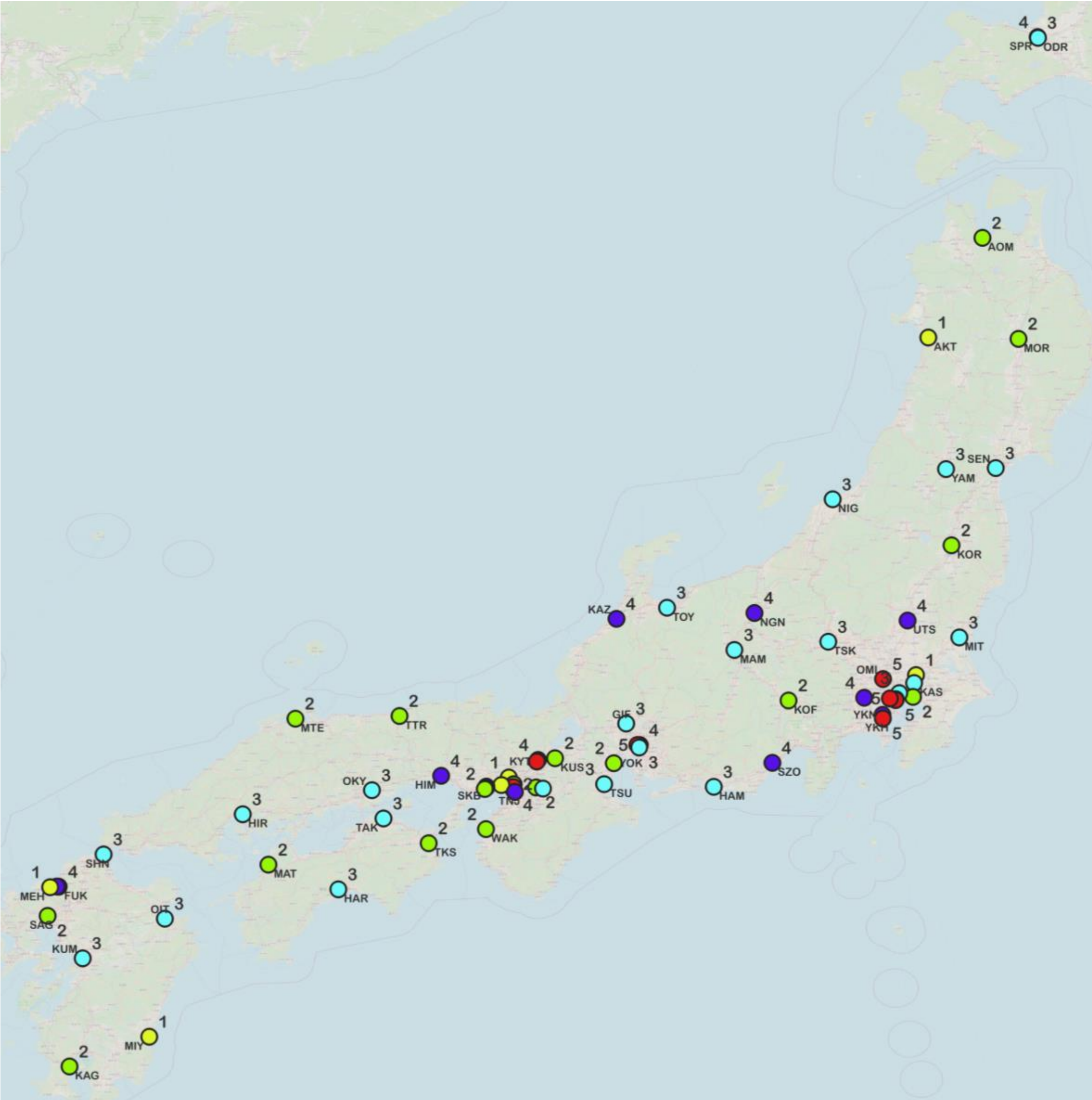

Figure 4.8 Distribution of the 5 different clustering groups on the map

This chapter conducted an in-depth analysis of short- and medium-term changes in station vitality using clustering techniques and mobile phone mesh data. We identified patterns and factors influencing station usage during the pandemic. Building on these findings, the next chapter will use multinomial regression analysis to further explore the impact of various factors on station dynamics, offering deeper insights into the predictors of demand loss and recovery.

Chapter 5 Explaining the station clustering with land-use and other characteristics

Having identified the types of changes in station dynamics, it is natural to wonder what factors influence which cluster a station is classified into. Building on the cluster analysis in the previous chapter, this chapter employs multivariate logistic regression modeling to understand the impact of various factors on station dynamics. This requires a comprehensive characterization of each station. We incorporate numerous variables, including land use, point of interest (POI) density, geography, and human factors, to explore their roles in predicting demand loss. Essentially, we aim to determine which factors, when present, can predict the magnitude of demand loss with high probability. For instance, we examine whether urban stations with higher densities of commercial and residential areas exhibit greater resilience compared to those primarily serving as transportation hubs. We also investigate whether stations in remote areas experience a significant decline in vitality due to the pandemic. By identifying key factors that influence station categorization, we provide valuable insights into the variability of station responses. This can help in developing targeted interventions to mitigate the impacts of future crises. The results of the analysis in this chapter will inform the long-term forecasting models discussed in the next chapter, allowing for more accurate predictions and better strategic planning.

5.1 Independent variables and indicators by cluster results

We now introduce different variables which we consider to be potentially suitable variables to explain the membership of a station in a particular cluster.

Government policies such as travel restrictions have a significant impact on transit demand. For example, when a region or country imposes travel bans or quarantine requirements on incoming travelers, the number of people traveling to that region may drop significantly. If restrictions are in place for a longer period of time, people may become accustomed to them and adjust their travel habits accordingly, resulting in a continued decrease in traveler demand.

As there is no mandatory travel ban in Japan, we can refer to the length of time each place is under a state of emergency. Depending on the region and the severity of the outbreak, the duration of the ranges from 28 to 48 days, with the three major metropolitan areas of Nagoya, Osaka and Tokyo, exceeding 40 days and being the latest to lift the state of emergency.

Station vitality in remote areas is likely less affected by travel restrictions. For one, there are less tourists and business travelers. Secondly, there have been less cases of COVID-19 in rural areas so that travelers might also be less concerned to travel.

We hence define six large cities based on geographic location and economic status, from north to south as important attractors of the trip and hypothesize that the distance to these will affect the COVID-19 impact: Sapporo, Sendai, Tokyo, Nagoya, Osaka, and Fukuoka. Tokyo, Nagoya and Osaka are the centers of the three biggest economic regions of Japan. Sapporo and Fukuoka are the largest cities on Hokkaido and Kyushu respectively. Sendai, as the largest city in the large North-eastern region is further added.

The farthest city from any of these major cities is Matsue City in Shimane Prefecture, 270 km from Osaka. The farthest city from all major cities on average is Kagoshima City, 890 km away on average, and the farthest city, Sapporo, is 1,500 km away.

Following our discussion in Section 4.3 we include population growth and economic development indicators. Higher population growth rates increase the demand for transportation services and people move more frequently. Economic development, demographic changes and environmental issues resulting from technological changes can also affect transit demand, such as the rise of teleconferencing and sustainable modes of transportation. We note that our data comes from the official publication of the Japanese government, where the smallest statistical unit is the city, ward, town or village so that we can also distinguish trends for different stations in the same metropolitan area. Furthermore, as noted, the MSS data includes information as to the percentage of people being registered in different prefectures. We use this information to obtain the percentage of the local population being present in the station mesh, where we define "local" as persons from the same prefecture the station is located in. (Assuming that the address used for registration is the same as the one where the person is living now.)

When public transit ridership decreases, stations with more lines connected to them may experience more of a decline because the station is an interchange point for multiple transit lines and riders will use it more. A decrease in ridership on one line can have a ripple effect on other lines connected to that station, leading to an overall decrease in ridership demand.

Table 5.1 shows the above discussed indicators as well as the population loss during the 10th week of the analysis period. This week has the lowest ridership and coincided with the Golden Week holiday within Japan, which overlapped with the government declared emergency, leading to a more severe ridership decline. (Otherwise, during public holidays many of the stations in our database are busy due to domestic tourism). It should be noted that the government dynamically adjusted the length of the emergency and lifted it once the number of cases fell below a certain threshold.

Looking at the patterns in Table 5.1 more closely, we firstly find that population density has the same increasing ordering as the COVID impact for Clusters 5 to 2, that is, stations in cities with higher population density are more impacted. This observation is in line with some of the literature discussed afore (Arimura et al., 2020; Rasca et al., 2021). The exception is Cluster 1, which has a higher population density than Clusters 2 and 3 but is less affected. We also consider the city growth in the last 5 years as an indicator as to how attractive the city is. We find that faster growing cities are more impacted, again with the exception of stations in Cluster 1. The information regarding the proportion of population over 65 years of age appears to be also useful: Cities with a larger degree older people tend to be slightly less impacted by the pandemic.

Also, the percentage of local travelers bears explanatory power: We can see a gradual decrease from Cluster 1 to Cluster 5, showing that stations with more local travelers are less impacted. Cluster 1 here does follow the trend.

In terms of station characteristics, the number of lines connected to the station can be approximated as gradually increasing from Cluster 1 to 5. All of the stations in Cluster 1 have less than four lines, while this is only true for nearly 60% of the stations in Cluster 2. All of the stations in Cluster 5 are served by more than nine lines. We also include some other factors in the table, such as distance to nearest city, which, if no other variable is controlled for, does show a less clear trend. In the following section we deepen this discussion with the support of regression analysis.

Table 5.1 Relevant indicators for each cluster

Indicators (All in average)	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
Population loss in week 10	12%	43%	56%	67%	80%
Days in state of emergency	36	31	30	37	43
MSS data in 2019	41781	69860	109154	206310	479055
Passenger ridership in 2019	51529	104969	174362	325719	1572628
Population of the area in 2020	289239	296842	493503	586598	2724896
Lines connected to the station	2.4	3.7	5.0	4.7	9.9
Population density / km^2	3770	2376	2939	7028	12473
Population change in 5 years	2.3%	-0.5%	0.2%	4.4%	8.2%
Population loss from 2020	-0.24%	-0.61%	-0.55%	-0.34%	-0.4%
People over 65 years old	26%	28%	27%	23%	20%
% local population in 2019	94%	92%	90%	85%	65%
Shortest distance to a big city	93	125	153	119	39

5.2 Land-use factors as explanatory variables

In order to improve the multinomial logistic regression model, we include additional geographic and socio-demographic variables: POIs, land use and a range of accessibility measures.

All available Points of interest (POIs) including landmarks and attractions, as well as station facilities are extracted. POIs must contain information such as name, category, longitude, latitude, elevation, etc. in order to be presented on an electronic map. We input the coordinates of the four vertices of the mesh where each station is located into OSM (Open Street Map) to extract and classified all the POIs within the mesh. To ensure the validity and analyzability, we only selected POI types with a large number as the object of analysis. The food and beverage category are the most numerous, followed by shopping places, public facilities, and transportation facilities. As an example, Fig. 5.1 shows the mesh map of Nagoya and Sapporo Station, and the small dots in the map are the various types of POIs.

The land use data contains the dominant land use status for 100*100m grids ("micro-meshes"), distinguishing following categories: rice fields, other agricultural land, forests, wasteland, high-rise buildings, factories, low-rise buildings, roads, railways, public utility land, open spaces, parks and green spaces, river areas and lakes, beaches, salt water areas, and golf courses. Since the mesh size of the station is 500*500m, there will hence be 25 site type data in each mesh, and we enter the ratio of each site type to the total area into the regression model. For illustration, in Fig. 5.2 the different site types are represented in different colors, such as railway (red), road (black), high-rise building (cyan), low-rise building (magenta) and vacant land (green). We can see that the ratio of railway to high-rise buildings is almost equal for the Osaka station area, while the Kyoto station mesh is mostly occupied by railway. This does not imply that the railway occupies more space but that it is the dominant factors for most micro-meshes. In Osaka, there are high-raise buildings near the tracks which are classified as dominant land-use for those micro-meshes. (We note that Kyoto City restricts high-rise buildings). There are even vacant areas (green) in the area around Sendai Station.

Figure 5.3 illustrates the number of land-use categories in the station mesh for various stations, showing significant variation depending on the station's geographic and urban context. Stations in more urbanized areas, such as Tokyo and Osaka, tend to have a greater number of categories, including high-rise buildings and dense road networks, which influence their resilience and demand dynamics during the pandemic. Conversely, stations in less urbanized areas show a different pattern of land-use distribution, which could contribute to differing levels of impact.

The accessibility of the station to other cities is considered in three main dimensions: minimum travel time, minimum travel distance and minimum travel cost. Due to the large number of stations in a metropolitan area, only the most important stations in several metropolitan areas are selected for the calculation in order to avoid bias in the weighting. This data mainly reflects the effect of station location on people's willingness to travel, as people travel more in areas that are convenient to travel to.

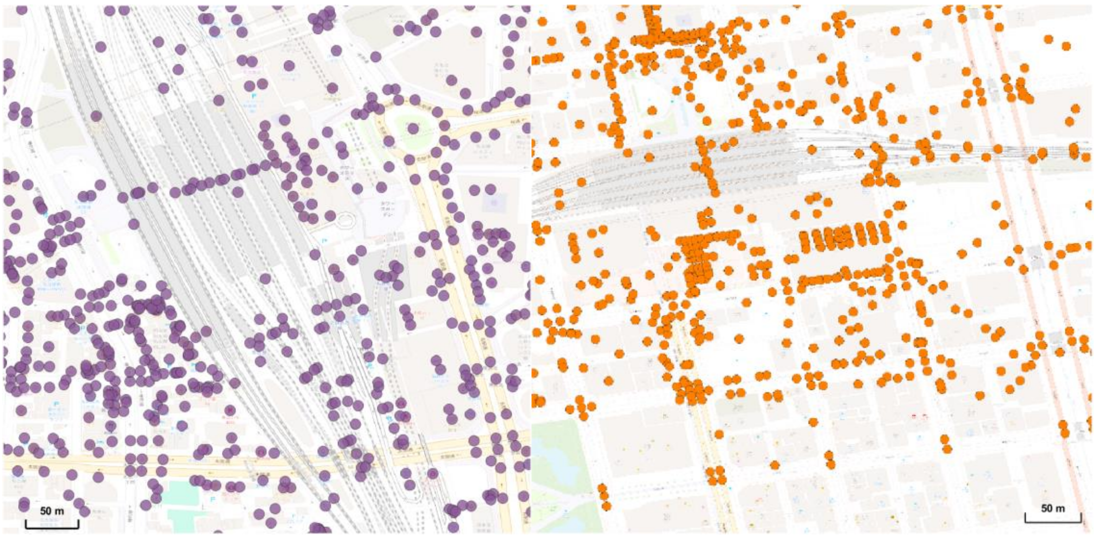

Figure 5.1 Station mesh map with POIs indicated as small dots, Nagoya station (left) and Sapporo station (right) as example

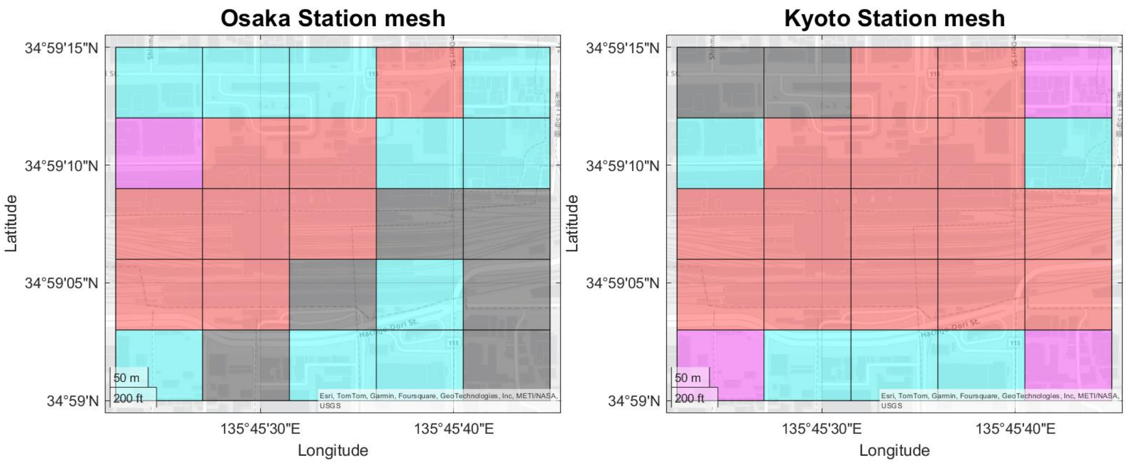

Figure 5.2(a) Land use of Osaka station (left) and Kyoto station (right)

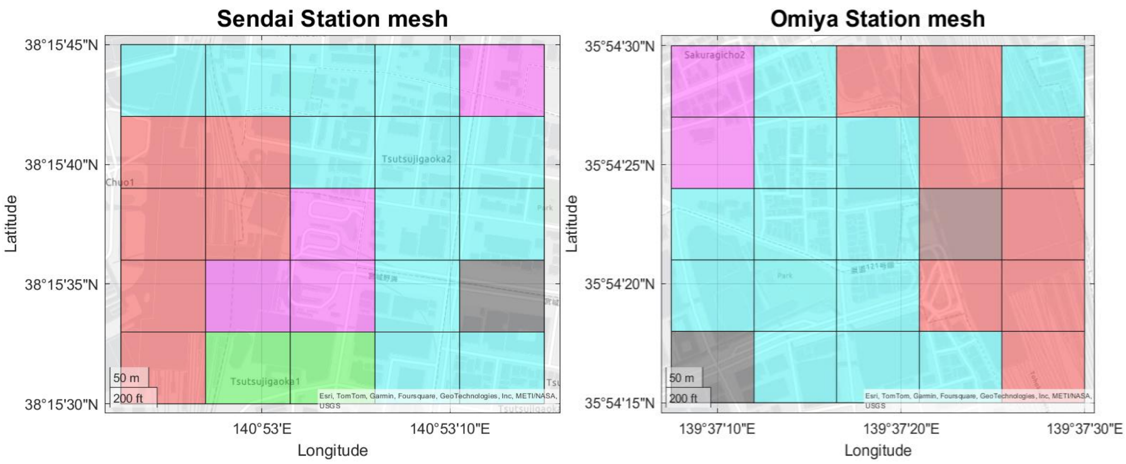

Figure 5.2(b) Land use of Sendai station (left) and Omiya station (right)

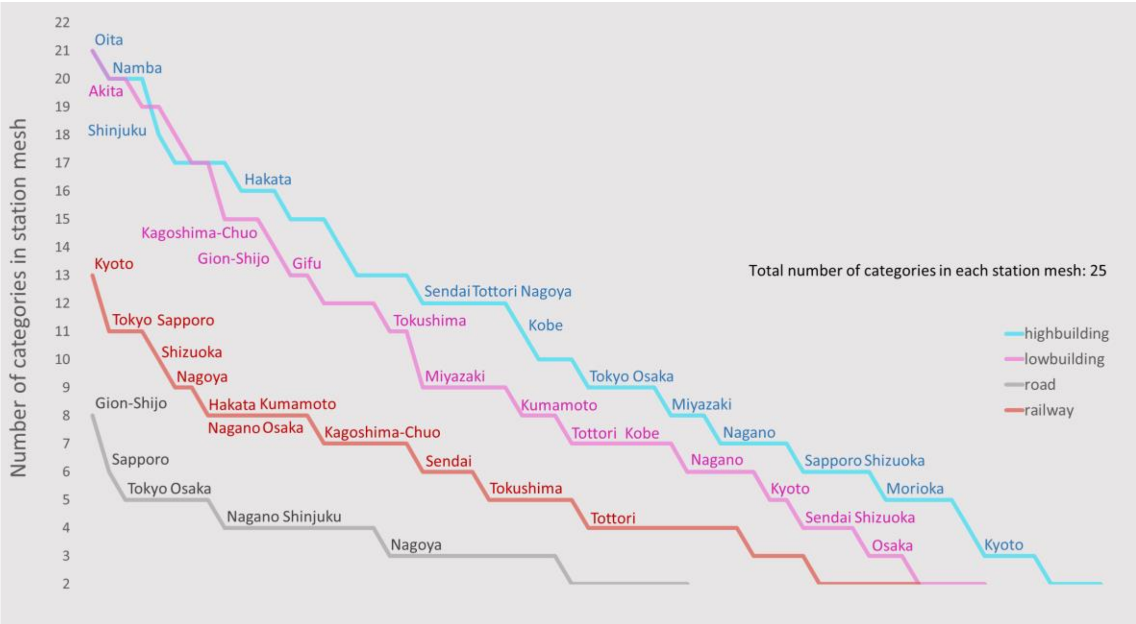

Figure 5.3 Distribution of land-use categories in station meshes across selected stations

5.3 Multinomial regression results

After obtaining the clustering result, we explore the factors of its variation. Since the dependent variable is categorical we employ multinomial logistic regression, an extension of binomial logistic regression, for predicting the probability of category membership based on multiple independent variables as in Eq. 5.1 and 5.2 (Hamid et al. 2018). Let S be the outcome of the clustering with $S = 0$ as the reference category and $k = (0,1, \dots, k-1)$. X is the set of independent predictor variables. Multinomial logistic regression allows for more than two categories of the dependent or outcome variable and requires consideration of sample size, outliers, and the ranking of the clustering results. The results we obtained after selecting appropriate variables for the regression model are shown in upper half of Table 5.2.

$$P(S = 0 \mid y) = \frac{1}{1 + e^{g_1(X) + \cdots + g_{k-1}(X)}} \tag{5.1}$$

$$P(S = k-1 \mid y) = \frac{e^{g_{k-1}(X)}}{1 + e^{g_1(X) + \cdots + g_{k-1}(X)}} \tag{5.2}$$

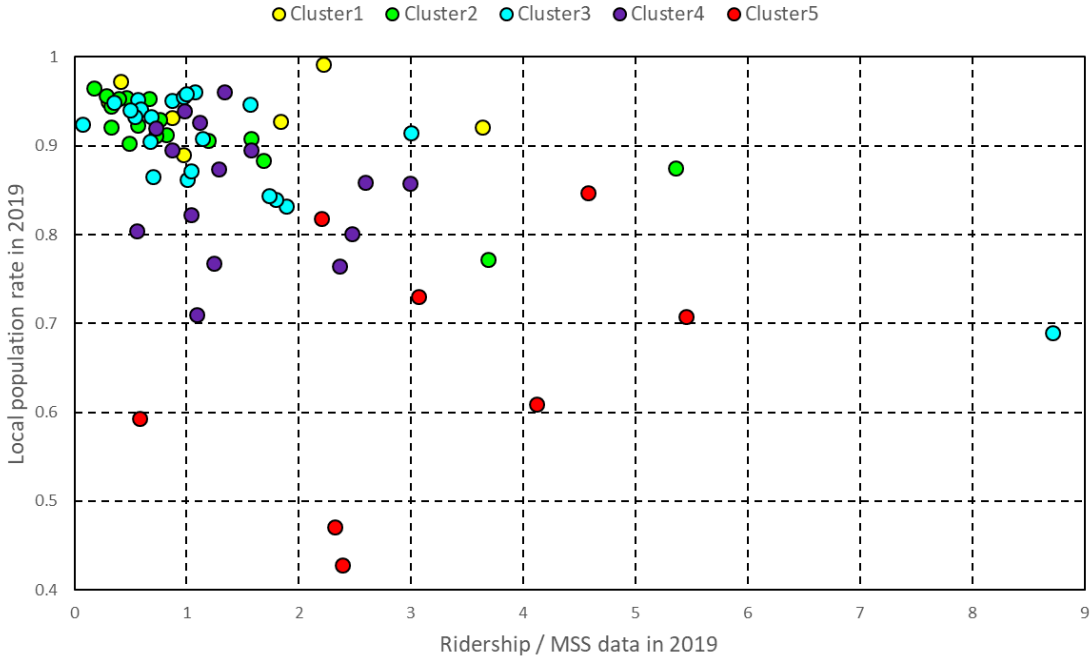

Figure 5.4 Ratio of two datasets and local population rate by different clusters

The results of the logistic regression model show that the number of lines and the rate of local population are more significant when distinguishing stations belonging to different clusters, provided that demand loss is used as a clustering condition. In general, demand loss will be larger in bigger cities and tourist cities than in other regions. We imply the latter by the fact that the percentage of the population from the local area has a significant positive impact on a city being not in Cluster 1. This is understandable given the restrictions during COVID-19.

We explore the relationship between ridership and MSS data further with Fig. 5.4. The horizontal coordinate is the ratio of ridership to the MSS data in 2019, which we can regard as a coefficient reflecting "station mobility" or "pass-through rate". This is because the shorter the traveler dwell time, the smaller the MSS data, but the ridership data remains the same. Thus, the higher the ratio the less the people stay in the station. Hence the data points in the lower right quadrant indicate stations where many non-local travelers pass through the station. Six of the eight stations in Cluster 5, which has the highest average number of lines and the highest demand loss, have a local rate of 0.7 and below. Further, we can notice that Cluster 5 stations tend to have lower local traveler rates and a higher Ridership/MSS ratio compared to the majority of the stations, illustrating the distinct characteristics of stations in this cluster. There is one outlier for Cluster 5 located in the lower left quadrant. This is

Ginza Station in Tokyo, and the location in the graph is possibly explainable by people visiting this station staying longer due to plenty of shopping opportunities in or nearby the station.

Table 5.2 Multinomial regression results with Cluster 5 as reference category. Top: Results estimated in original model. Below: improved results

Variable	Unit	Cluster1	Cluster2	Cluster3	Cluster4
Regulation days	day	-0.001	-0.126	-0.181	-0.108
Lines serving	/	-2.727***	-1.451***	-1.081***	-1.295***
Population change	%	0.208	-0.329	-0.202	-0.191
Age over 65	%	0.204	-0.056	0.034	-0.190
% local population	%	74.72***	28.397**	21.52**	18.67*
Distance to big cities	kilometer	-0.0004	-0.0004	0.0015	0.003
Pseudo R^2		0.658			
Improved results					
POI - Convenience	/	-1.645***	-0.230	-0.250*	0.938***
POI - Bank	/	-8.668***	-0.783**	-0.304	-1.061***
POI – Public Toilets	/	3.612***	0.456	0.639	-1.078**
POI - Supermarket	/	5.348***	1.679**	1.035*	0.780
Land use - Road	%	-223.6***	-119.4***	-106.6***	114.49***
Land use - Railway	%	-228.9***	-66.32***	-62.72***	26.33**
Time to Tokyo	minute	-0.119***	0.135***	0.136***	-0.047**
Distance to Nagoya	kilometer	0.013**	-0.004	-0.002	0.002
% local population	%	134.1***	27.84*	21.20*	-9.296
Lines serving	/	-8.297***	-3.247***	-2.673***	-6.695***
Pseudo R^2		0.774			

The reason why the tightness of COVID-19 controls which generally determines people's willingness to travel is not significant in the results to explain the clusters may be because the difference in the length of controls between cities is not large (about two weeks). The amount of population changes over the last 5 years and the percentage of the population over 65 years old are similar in the regression results, but are also not strongly associated with ridership loss. The distance of the station from the nearest large city also apparently does not have much effect on ridership change, a conjecture introduced based on the attractiveness of large cities to small and medium-sized cities, but distance is not the only factor.

Following data preparation of the various POIs and land-use variables and other station characteristics, to avoid multicollinearity issues, we remove a number of variables before proceeding. Utilizing correlation analysis, variance inflation factors and intra-cluster variance, those variables having lower correlations are retained with backward stepwise analysis. Having obtained a manageable set of variables we turn to forward stepwise analysis.

For this we take the original model as basis and sequentially add variables that are not in the current model and select the variable that improves the R-squared value of the model the most, while ensuring that all variables in the model are significant in at least one cluster. This step continues until the algorithm no new variables that are both significant and not overly correlated with the current variables are found. After repeated trials, the model with the largest R-squared value, i.e. the final model, is obtained. The results of the model are shown in lower part of Table 5.2. The coefficients represent the effect of the predictor variables on the log odds of entering a category versus the log odds of entering the reference category.

With the introduction of additional explanatory variables, we can observe that the most important variable contributing to the loss of vitality in the previous model changes from the number of lines to the proportion of road and railway around the station, and its significance is specifically large for Clusters 1, 2 and 3. These two land use variables reflect the size of the station and, indirectly, the number of people and the radius it can serve. In COVID-19, the larger the area covered by the station, the greater the population loss, as is the case in Tokyo and Osaka. Road has an even larger influence, which can also be explained. Stations with a higher proportion of roads in the mesh have fewer other activities, carry more passengers, and move in and out of the station more efficiently, and tend to be less likely to have people stay in the area for long periods of time. Thus, stations with better road access are more vulnerable to experience demand loss. A third variable that is related to the size of the station is the number of lines by which the station is served. Compared to the original model it decreases in weight but it remains a significant variable for all four clusters and confirms that larger stations experience more demand loss.

The share of local population visiting the station is significant for Clusters 1, 2 and 3. The more locals use the station, the more active the station remains during the pandemic. On further investigation we find that stations with high share of local passengers can be either neighborhood stations (where people have to make basic journeys also during the pandemic) or interchange stations (where passengers stop for a short time without much connection to the surrounding area).

We can also find that some POIs and geographical factors are determinants of cluster membership. We do clearly not imply causality for these independent variables, but include them as proxy to characterize the meaning of the station for the city and the land-use around the station. The number of banks around the station is significant in Cluster 1 and 2, suggesting that the lower the number, the more likely the station is to be in these clusters. In other words, stations that are in areas where financial activities are an important business are more affected. Further, we find that the presence of supermarkets and convenience stores to some degree characterizes the stations with the effect of the number of convenience stores being opposite to that of the number of supermarkets. Convenience stores are usually visited by people for shorter periods of time and are more frequented by travelers changing trains. Supermarkets, on the other hand, are more likely to be visited by locals and stay for more time. It is hence understandable that stations with supermarkets in their vicinity tend to be more robust to activity loss during COVID. Related to this explanation we also include the number of public toilets in the model. We interpret their presence as indicator of people staying usually for longer time in and around the station. It is therefore understandable that stations frequented by people for various reasons are more robust to the pandemic than stations where people only briefly come and go.

To understand if the network location of the station is also an indicator of robustness we further tested the inclusion of distance and travel time to major cities in Japan and retained distance to Nagoya (the third major city and in the geographic center of Japan) as well as travel time to Tokyo. Time to Tokyo is significant for all clusters but with a difficult to interpret tendency. The least affected stations tend to have a lower travel time to Tokyo. Stations in Clusters 2 and 3 tend to be further away whereas stations in Cluster 4 tend to be again closer to Tokyo. The effect is small but significant. Looking at Fig. 4.8, Cluster 4 stations tend to be regional fairly large cities in central Japan. Their stations have suffered significantly due to less interregional activities, possibly including interactions with Tokyo. Regarding distance to Nagoya, we find a positive effect for Cluster 1. In other words, stations far away from the center to Japan tend to be slightly less impacted. Reasons could be that a) COVID-19 restrictions were less strictly obliged and that these regions experience less long-distance travel that was hit hardest during COVID-19.

Overall, it can be concluded, that the interpretability and richness of the model increases with the additional variables. Also, the R-squared value increases by 0.12 to 0.77. We also emphasize that all variables are significant for Cluster 1 and only the number of lines is significant for Cluster 4. This reflects the fact that, with the exception of Cluster 1, the other clusters are not as differentiated from Cluster 5 as Cluster 1. The results of the multivariate explanations reflect the importance of site size and local population on the one hand, and the fact that the two are not very compatible on the other. In terms of the general trend of current development, hub stations in large cities are bound to attract large numbers of people from surrounding regions, which is an important feature of metropolitan areas. This polarization becomes more pronounced as the demographic gap between cities widens.

This chapter utilized multinomial regression analysis to examine the impact of land-use factors and other variables on station vitality. This detailed examination identified significant predictors of demand loss, providing valuable insights for targeted interventions. The next chapter will extend this analysis to long-term forecasting methods, evaluating techniques like ARIMAX and LSTM to predict post-pandemic public transportation usage.

Chapter 6 Long-term forecasting of vitality recovery

In the previous chapters, we have analyzed trends in station vitality and explored the factors influencing these trends. We also examined how to assess the level of vitality of a station in the post-pandemic era. The next logical step is to determine how we can use existing data in conjunction with long-term forecasting methods to obtain a reference value and validate it with real-world situations. This chapter evaluates the effectiveness of mainstream time-space series long-term forecasting models, such as ARIMAX and LSTM, in capturing complex demand dynamics and predicting the recovery of station vitality. We consider external factors such as policy impacts and demographic changes in our analysis. While the forecasting logic of these approaches varies, their goal is similar: capturing the hidden patterns in the available data. The predictive results of these models are critical to understanding long-term trends in station vitality. By utilizing these models, we can provide public transportation operators with insights that inform their planning and decision-making processes. This understanding of long-term trends will be crucial in the next chapter, where we focus on strategic planning and operational adjustments based on the forecasted data.

6.1 Time-series forecasting methods

As can be seen in Fig. 6.1, the different clusters that were defined based on the demand loss during the first wave, maintain essentially the same order in subsequent waves. After the first wave Clusters 1, 2 and 3 can recover fairly quickly to nearly the original level of demand after being affected. Instead Clusters 4 and 5 can only recover to a level that is still 10 to 20% lower than before the wave. They only recover to nearly the pre-pandemic level the following summer.

For the following waves the stations are all less affected but the relative impact among the clusters is in line with that observed for the first wave. Looking at the end of the observed period it is noteworthy that Cluster 1 even exceeds the pre-COVID-19 level of activity. Clusters 2, 3 and 4 have recovered to nearly pre-pandemic levels whereas Cluster 5 has not.

This figure also shows the number of COVID cases. The first, important, though in terms of number small, wave of cases precedes the loss in activity slightly due to policies coming in effect as a response of the cases being observed. For the subsequent waves the activity loss and peak in COVID-19 cases occur almost simultaneously. It is important to note that the number of cases continues to increase in subsequent waves, but that the impact on station demand decreases. Therefore, also the number of cases is only a weak indicator of station demand loss.

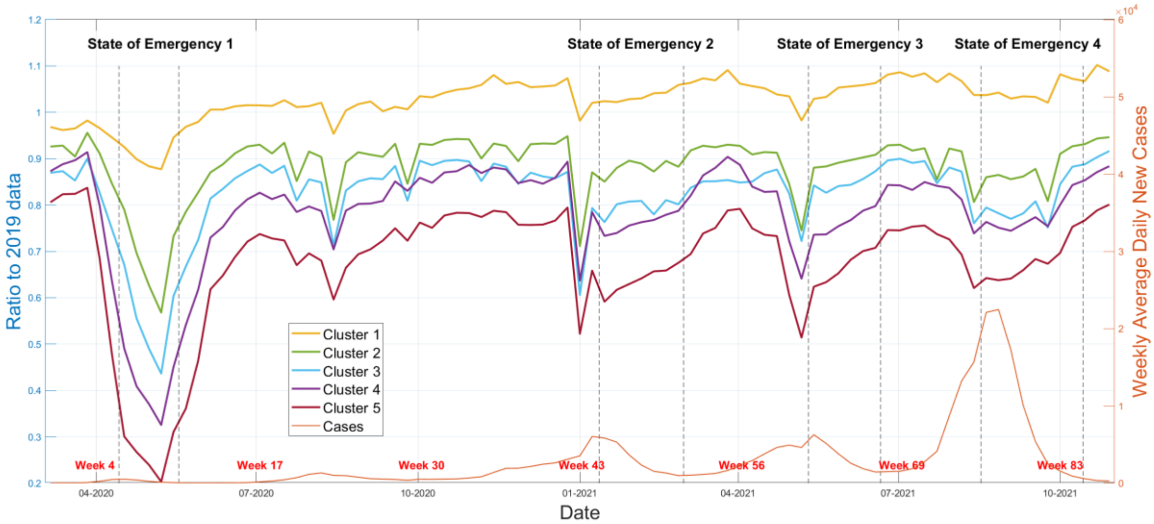

Figure 6.1 Changes in viability of each cluster over a long-term period

6.1.1 ARIMAX (autoregressive integrated moving average with exogenous variable)

Firstly, Autoregressive Integrated Moving Average (ARIMA) models are tested. These models are denoted as ARIMA (p, d, q), where p is the order of autoregression, representing the number of lag observations included in the model; d is the degree of differencing, indicating the number of times the series needs to be differenced to achieve stationarity; q is the order of the moving average, representing the size of the moving average window. Examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) helps identifying the moving average (MA) order (q), and the autoregressive (AR) order (p). In the Fig. 6.2 we use Cluster 5 as an example and plot these which suggest that p = 1 and q = 2 are appropriate. Further we find that stationarity of the sequence has been best at d = 1. On the fitting results, we find even after multiple test that ARIMA does not fit well as COVID-19 is not periodic. As shown in Fig. 6.7, we observe low R-squared values and the maximum does not reach 0.2.

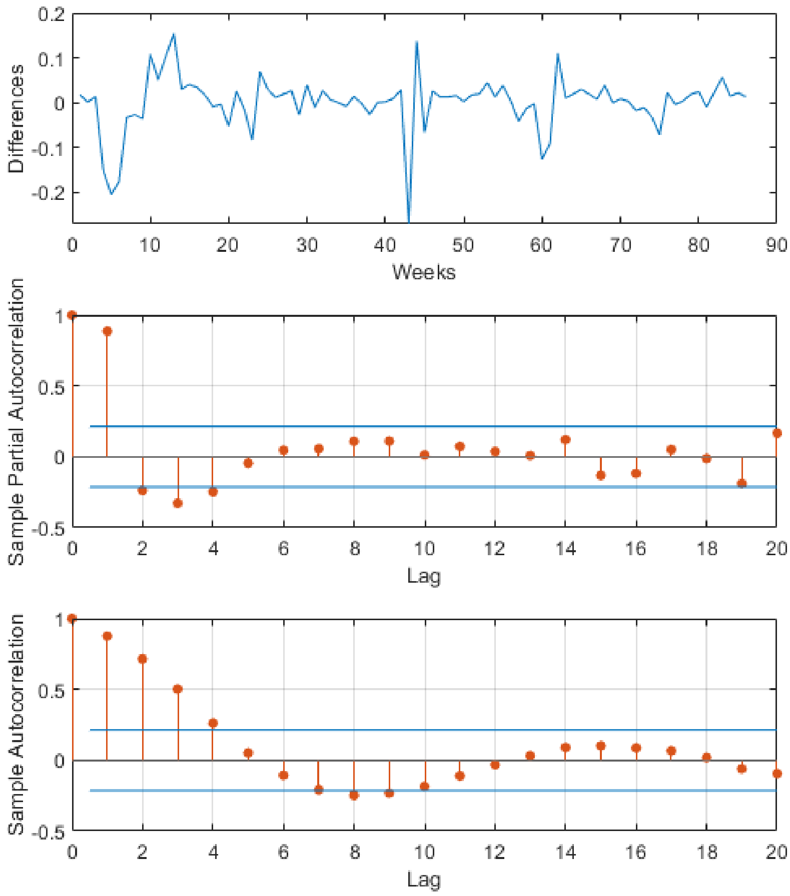

Figure 6.2 d =1, PACF and ACF of Cluster 5

The ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variables) model extends the basic ARIMA model by incorporating external or exogenous variables that can influence the time series. This is particularly useful when there are additional factors outside the time series itself that impact its behavior. We test the number of new cases per day and the proportion of people affected by COVID-19 restrictions and associated policy measures as exogenous variables for our research. These two factors are presumed to capture the irregular patterns of the COVID-19 waves and might also indicate the magnitude of the to be expected station activity loss.

The ARIMAX model can be expressed with the following equations:

$$y_t = \alpha + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{k=1}^{m} \beta_k X_{k,t} + \epsilon_t \tag{6.1}$$

$$\epsilon_t = y_t - \widehat{y_t} \tag{6.2}$$

Where:

y_t the response variable (station vitality) at time t (observed)

$\widehat{y_t}$ the predicted y at time t given by the ARIMAX model

α a constant term, the intercept of the model, accounting for any non-zero mean in the time series

$\emptyset_i$ the autoregressive (AR) coefficients, represents the influence of past values of the response variable

θ_j the moving average (MA) coefficients, represents the influence of past error terms

ϵ_t the error term at time t, represents the random noise in the data. It is dynamically calculated during the model fitting and forecasting processes

β_k the coefficients for the exogenous variables $X_{k,t}$

For a single exogenous variable (p = 1, d = 1, q = 2):

$$y_t = \alpha + \emptyset_1 y_{t-1} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \beta_1 X_{1,t} + \epsilon_t \tag{6.3}$$

For two exogenous variables (p = 1, d = 1, q = 2):

$$y_t = \alpha + \emptyset_1 y_{t-1} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \epsilon_t \tag{6.4}$$

Where:

$X_{1,t}$ the number of new COVID-19 cases per day (log10 transformed) or the proportion of people affected by COVID-19 restrictions

$X_{2,t}$ another exogenous variable

The number of new cases per day has been shown in Fig. 6.1 and is based on the number of official announcements. Estimating the number of persons affected by COVID-19 is more difficult and we make following assumptions roughly based on previous literature: We consider that in the early weeks of the pandemic, despite some unease in the general population, before the declaration of the emergency, only a low number of people are affected in their activity patterns and we set this percentage at 10%. Then the state of emergency brought most of public life to a standstill and we set the affected value to 80%. Though not using data from Japan, we also refer to Hasselwander et al.

(2021) and Aloi et al. (2020), who analyzed the loss of mobility of populations in cities using mobile device data and found a mobility loss of -74.5% and -76%, respectively.

Taking into account political lags and changing attitudes towards emerging epidemics, we assume that the proportion of the population affected after the first emergency depends on the length and order of subsequent emergency declarations. All values were set to be as nonreplicating as possible to try to reflect the overall trend during the epidemic. We presume that the impact of each subsequent emergency declaration is decreasing by 10% so that there is a level of 50% at the fourth emergency declaration. One can argue whether a lower or higher decreasing impact is rationale, but clearly with each subsequent declaration less persons were concerned and furthermore some restrictions were less severe. For a more detailed discussion on the impact of different states of emergency in Japan, refer to Sun et al. (2022), which uses Google trends data to reflect results under different policies.

For the three "quasi-state of emergencies" we presume that their impact is halved, meaning that 40% are impacted for the first quasi-emergency declaration. During these states some restrictions of previous full state of emergency declarations were reduced. Unlike states of emergency, which are broader, more centralized measures introduced at the national level, quasi-emergencies are more localized and flexible, used mainly by local authorities to target parts of the region with a high number of new cases. The main difference is the partial lifting of restrictions on opening hours, alcohol selling and partying. We presume that the impact remained at 40% for the second state because of its proximity to the first, and adjusted it to 30% for the third. As a result of the "Go-To Travel" campaign, which encourages people to travel, the proportion affected during this period will be lower than the minimum during any state or quasi-state of emergency, so that we set it to 30% before and after the campaign. During the campaign, as COVID-19 was still present, the value is likely to be larger than the 10% but will be reduced so that we suggest a value of 20% is appropriate.

Fig. 6.3 illustrates the affected proportion and timeline. We acknowledge that it can be argued whether the values should be smaller or larger and hence conduct a sensitivity analysis to different assumptions. Clearly including this information in a forecasting model is also an acknowledgement that the COVID-19 patterns are so irregular that its impact is difficult to explain without such information. We are hence interested in understanding in how much better the ARIMAX model performs compared to the ARIMA model that only includes "internal" information.

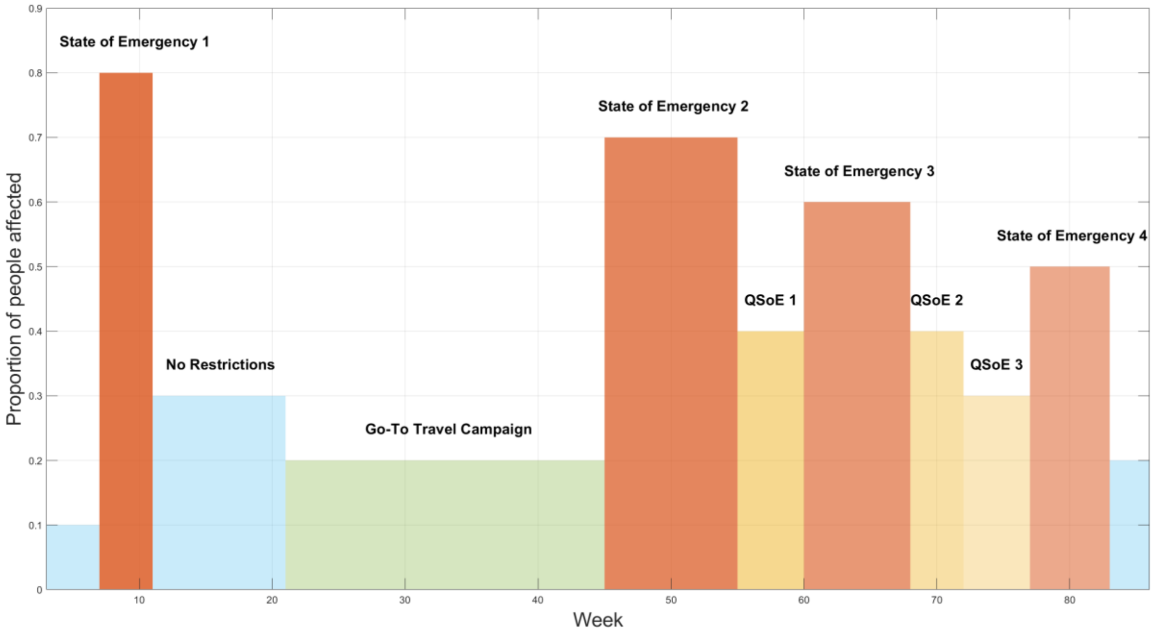

Figure 6.3 Proportions of people being affected within investigation time window by different polices (QSoE denotes quasi-state of emergencies)

To test the robustness of this assumption, we changed the first State of Emergency setting from 80% to 70% and 90%. Testing different settings for the affected population variable, as shown in Fig. 6.4, revealed minimal variation in results, indicating the robustness of our assumptions. This supports the reliability of our model in predicting station vitality under various scenarios. Additionally, these tests reinforce the flexibility of our model, demonstrating that it can accurately reflect station vitality trends even when key variables are adjusted. This flexibility is crucial for ensuring that our model remains valid across a range of potential real-world conditions, further enhancing its applicability for long-term forecasting.

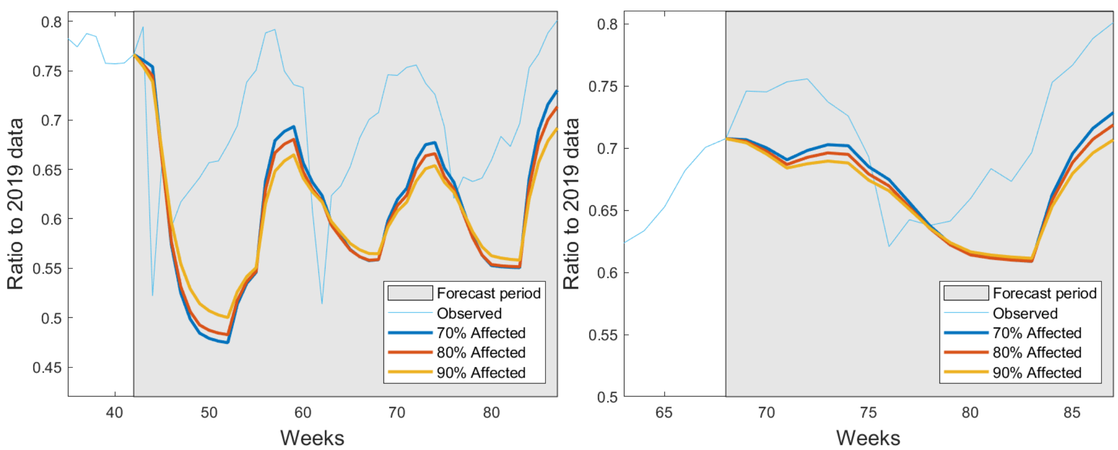

Figure 6.4 Cluster 5 by different affected proportion with 50% training (left) and 80% training (right)

6.1.2 LSTM (long short-term memory)

As a third alternative we test LSTM approaches. This recurrent neural network (RNN) approach is designed to solve the "gradient vanishing problem" that prevents traditional RNNs from being trained on long sequences (Hochreiter et al., 1997). The LSTM introduces a memory unit and three gates (a forgetting gate, an input gate and an output gate) that allow the network to selectively remember or forget information over time. This architecture allows the LSTM to capture and learn long-range dependencies in sequential data. For our application, we suggest it might help us to capture the irregular and diminishing COVID-19 impact. In particular the population might learn that it can "forget" the first stage during the latter, less severe stages. The LSTM network constructed according to the characteristics of the data used is shown in Fig. 6.5.

1) Sequence Input Layer: This layer accepts the sequential data as input. It is the first layer of the network that takes the time-series data, which includes historical passenger demand and exogenous variables
2) LSTM Layer: The core of the network, this layer consists of memory cells and gates that manage the flow of information. It captures the temporal dependencies in the data, enabling the network to learn from long sequences
3) Dropout Layer: This regularization layer helps prevent overfitting by randomly setting a fraction of the input units to zero at each update during training. This encourages the network to learn more robust features
4) Fully Connected Layer: This layer connects every neuron in the previous layer to every neuron in the next layer, transforming the learned features into the final output
5) Regression Layer: The final layer, which outputs continuous values, suitable for predicting the demand values in our time-series forecasting task

In summary, the three models have different emphases: ARIMA is a classical statistical model that assumes a linear relationship between past observations and future forecasts. It requires the time series to be static, which makes it difficult to capture complex patterns. ARIMAX extends ARIMA by adding exogenous variables that allow it to consider other factors that affect the time series. This is useful when the exogenous variables have a significant impact on the patterns in the data. LSTM is a deep learning model that excels at capturing complex non-linear relationships in time-series data. LSTM is particularly useful when dealing with sequences that have long dependencies and involve complex patterns. The choice between these models depends on the specific characteristics of the data, the nature of the problem, and the available computational resources. The ARIMA model is computationally efficient and explanatory, while the ARIMAX and LSTM models are more flexible in dealing with complex relationships and external factors.

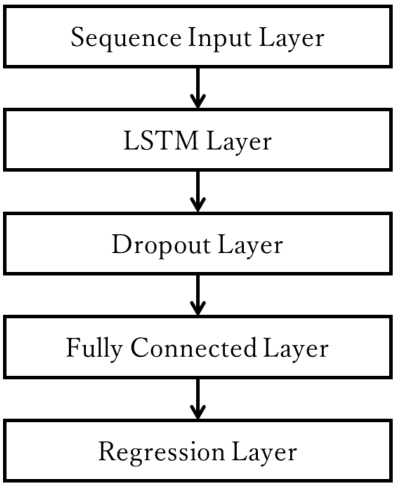

Figure 6.5 Flowchart of the tested LSTM network

6.2 Time-series forecasting results

6.2.1 ARIMA and ARIMAX parameters and sensitivity

Table 6.1 shows the results of the ARIMAX model for the Cluster 5, training percentage 80% parameter setting, and Fig. 6.6 shows the results of the ARIMAX model using only the number of cases, only the proportion affected, and a combination of both. The results using only cases are less favorable, and the results combining the proportion affected with the number of cases are almost identical to using only the proportion affected. This suggests that the number of cases does not improve the model. Therefore, in subsequent methodological comparisons, we only use the proportion affected as an exogenous variable for ARIMAX.

Table 6.1 Cluster 5 with 80% training results of the ARIMAX model

Parameters-ARIMAX	Coeff.	t-Statistics	p-Value
Constant	0.33	3.15	<=0.01
AR (1)	0.62	4.72	<=0.001
MA (1)	0.12	1.06	0.29
MA (2)	0.23	1.16	0.25
Beta (1)	-0.22	-2.39	<=0.05
Variance	<=0.01	5.15	<=0.001
R^2	0.534		

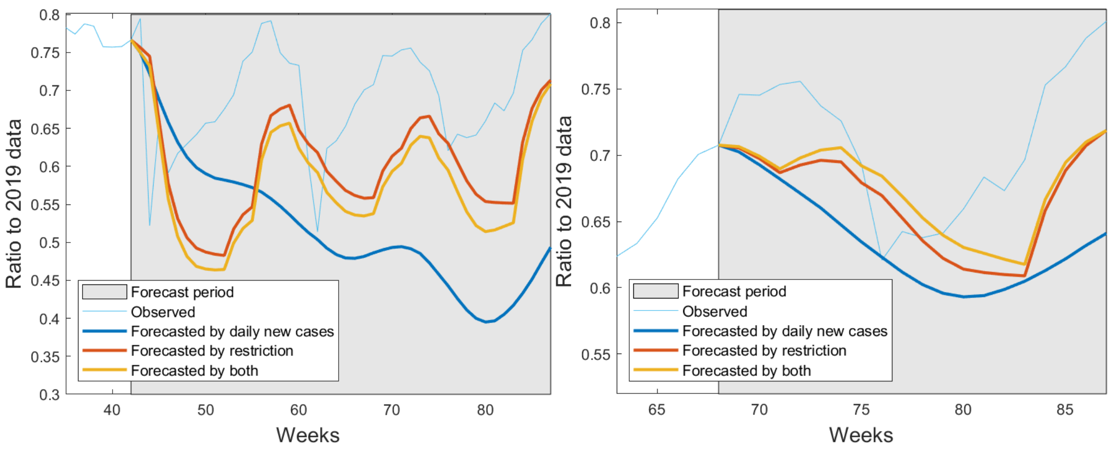

Figure 6.6 Cluster 5 by different exogenous variables with 50% training (left) and 80% training (right)

6.2.2 Comparison of different methods

We use R-squared and RMSE (Root Mean Square Error) to assess the accuracy of the models. RMSE is more sensitive to large errors or outliers as a large prediction error can significantly affect the overall RMSE value.

We test the effectiveness of LSTM at different levels of learning by varying the training ratio in the settings, which are 50%, 60%, 70%, and 80%, respectively. The number of the learning epochs (MaxEpochs) needs to be determined through experiments and model performance monitoring, as too large values can lead to overfitting and less prediction power. We test 1 to 500 iterations, and observe that the R-squared and RMSE values of the five clusters reach a more balanced value around a MaxEpoch value of 150. Cluster 1 fluctuates but remains stable after 200, whereas Cluster 3 has a drop-off point at around 300 iterations and Clusters 4 and 5 remain stable for larger iterations. However, no improvements can be found for MaxEpoch values larger than 150.

As can be seen in Fig. 6.7, clearly the accuracy increases as the training percentage increases. Further, generally, the accuracy of the three methods gradually increases from ARIMA to ARIMAX to LSTM, indicating that LSTM achieves a better prediction.

It is important to observe, however, that LSTM performs bad if the training percentage is not sufficient, in our case 50%. This can be explained by referring back to Fig. 6.1. The percentage of decrease in the first wave is significantly higher than in the other waves. If the training period is too short, the forgetting gate has not had enough information to process the information from the first wave, resulting in a greater shift in the predicted values. In addition, the LSTM prediction value of Cluster 3 is only slightly better at 70% and 80% training, and all the others are worse than ARIMAX and ARIMA. This may be due to the fact that the original sequence of Cluster 3 fluctuates significantly more during demand loss and recovery. Therefore, the prediction for station vitality in this cluster appear to perform better with ARIMAX, whereas LSTM is suitable for smoother sequences with more pronounced trends.

We select the unique Cluster and, once more, Cluster 5 for further analysis and illustration. Cluster 5 has the highest R-squared value among the five clusters and the final prediction effect of the three methods are shown in Figures 6.8 and 6.9. It can be seen that the result of the ARIMA model is almost a straight line for both clusters. The prediction result of the ARIMAX model has deviation and delays from the true data, but the trend of change is correctly predicted. This shows that the affected proportion is an important factor, that is, people's willingness to travel is impacted by the state's state of emergency policies. Instead, the LSTM model, which we remind does not have exogeneous variables, can perform well, but its robustness can be disputed as it depends on the training period and hence the assumption that the overall nature of the phenomena continues. Fig. 6.10 shows the prediction results of different clusters at the same training percentage (80%). The LSTM performs best, and the ARIMAX performs well except for Cluster 1, with a slight delay in the prediction of the recovery period.

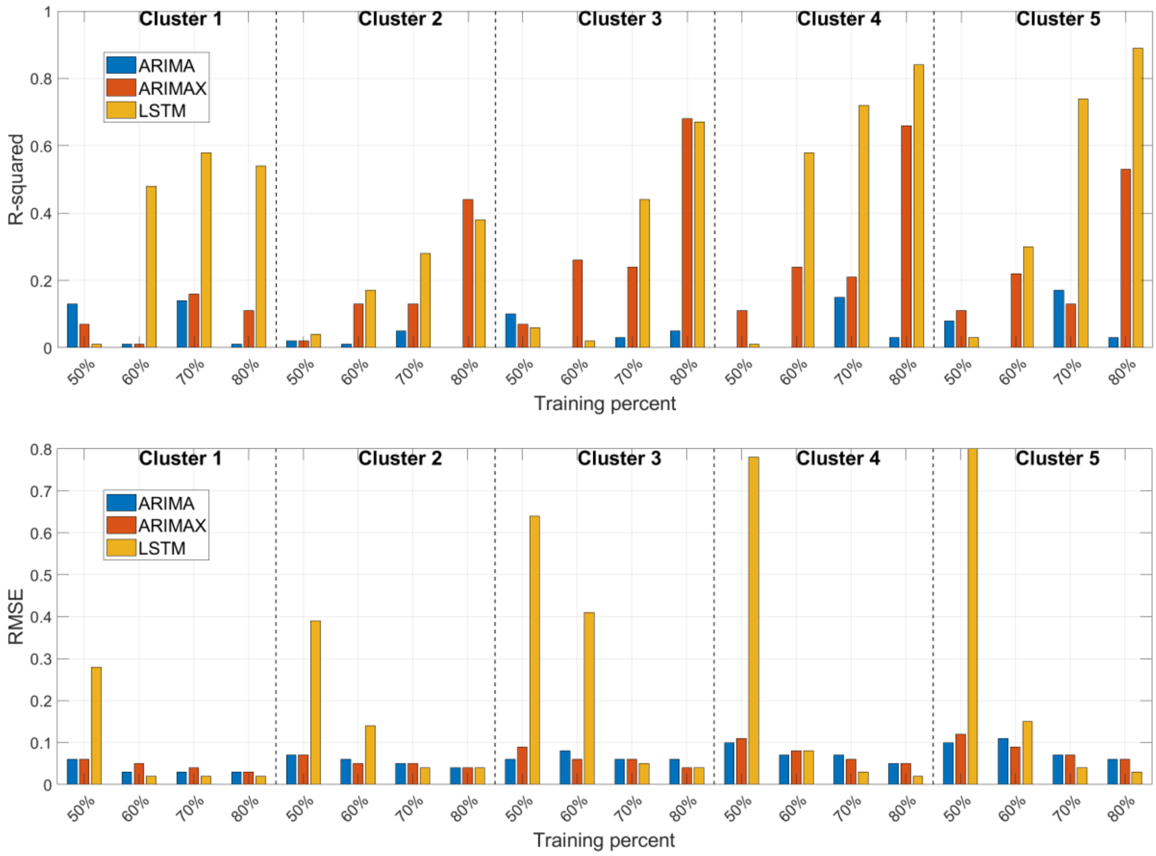

Figure 6.7 R-squared (top, larger values preferred) and RMSE (bottom, lower values preferred) for the five clusters and different training percentage

Table 6.2 R-squared and RMSE values for the five clusters and different training percentage (best model in bold)

Cluster No.	Training %	R-squared			RMSE		
		ARIMA	ARIMAX	LSTM	ARIMA	ARIMAX	LSTM
Cluster 1	50%	**0.13**	0.07	0.01	**0.06**	**0.06**	0.28
Cluster 1	60%	0.01	0.01	**0.48**	0.03	0.05	**0.02**
Cluster 1	70%	0.14	0.16	**0.58**	0.03	0.04	**0.02**
Cluster 1	80%	0.01	0.11	**0.54**	0.03	0.03	**0.02**
Cluster 2	50%	0.02	0.02	**0.04**	**0.07**	**0.07**	0.39
Cluster 2	60%	0.01	0.13	**0.17**	0.06	**0.05**	0.14
Cluster 2	70%	0.05	0.13	**0.28**	0.05	0.05	**0.04**
Cluster 2	80%	0.00	**0.44**	0.38	**0.04**	**0.04**	**0.04**
Cluster 3	50%	0.10	**0.07**	0.06	**0.06**	0.09	0.64

Cluster 3	60%	0.00	**0.26**	0.02	0.08	**0.06**	0.41
Cluster 3	70%	0.03	0.24	**0.44**	0.06	0.06	**0.05**
Cluster 3	80%	0.05	**0.68**	0.67	0.06	**0.04**	**0.04**
Cluster 4	50%	0.00	**0.11**	0.01	**0.10**	0.11	0.78
Cluster 4	60%	0.00	0.24	**0.58**	**0.07**	0.08	0.08
Cluster 4	70%	0.15	0.21	**0.72**	0.07	0.06	**0.03**
Cluster 4	80%	0.03	0.66	**0.84**	0.05	0.05	**0.02**
Cluster 5	50%	0.08	**0.11**	0.03	**0.10**	0.12	0.80
Cluster 5	60%	0.00	0.22	**0.30**	0.11	**0.09**	0.15
Cluster 5	70%	0.17	0.13	**0.74**	0.07	0.07	**0.04**
Cluster 5	80%	0.03	0.53	**0.89**	0.06	0.06	**0.03**

We evaluated long-term demand forecasting methods, highlighting the effectiveness of ARIMAX and LSTM models in capturing complex demand dynamics in this Chapter. These insights are crucial for optimizing service frequencies and resource allocation. In the next chapter, we will synthesize these findings to develop a theoretical model for balancing service quality and operational constraints during the COVID-19 pandemic, guiding PT operators in making informed decisions to maintain long-term demand and operational stability.

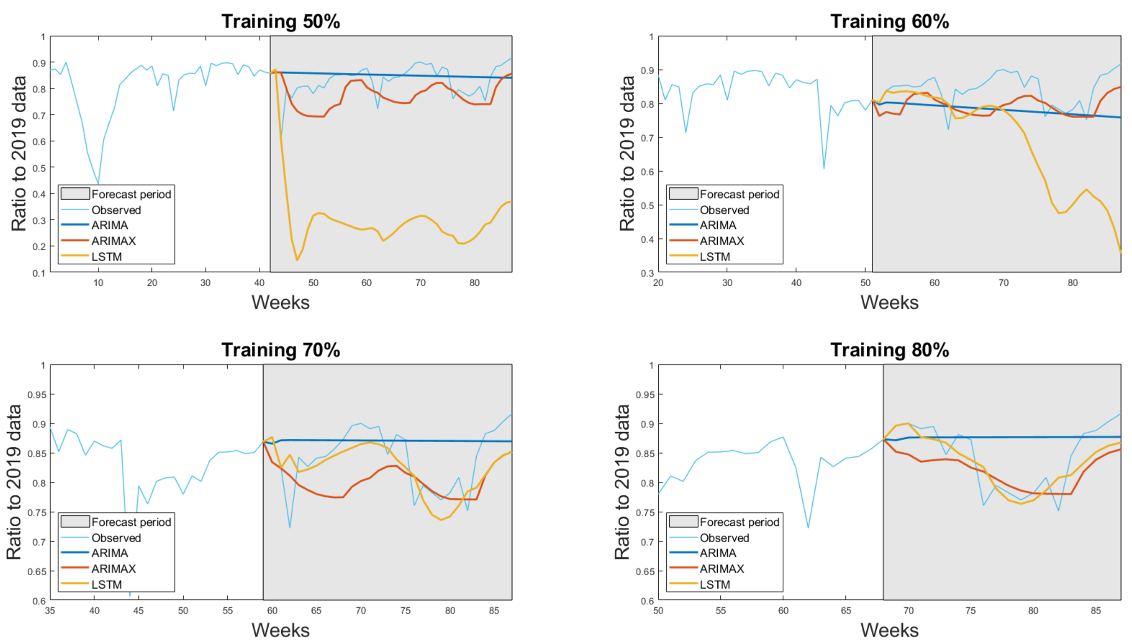

Figure 6.8 Observed and forecast of Cluster 3 with different training percent

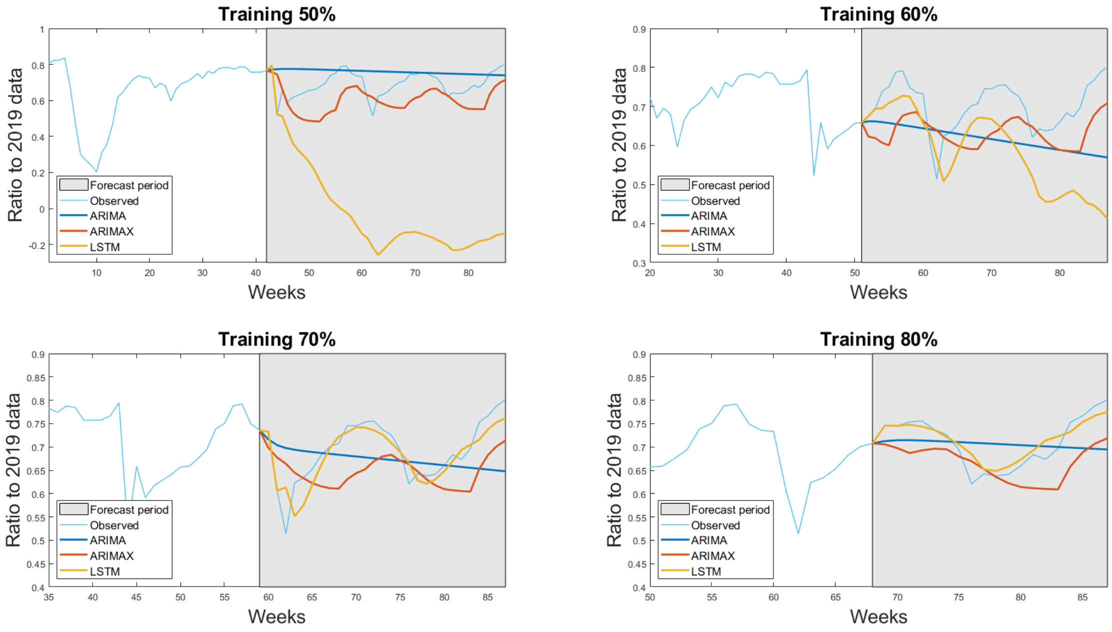

Figure 6.9 Observed and forecast of Cluster 5 with different training percent

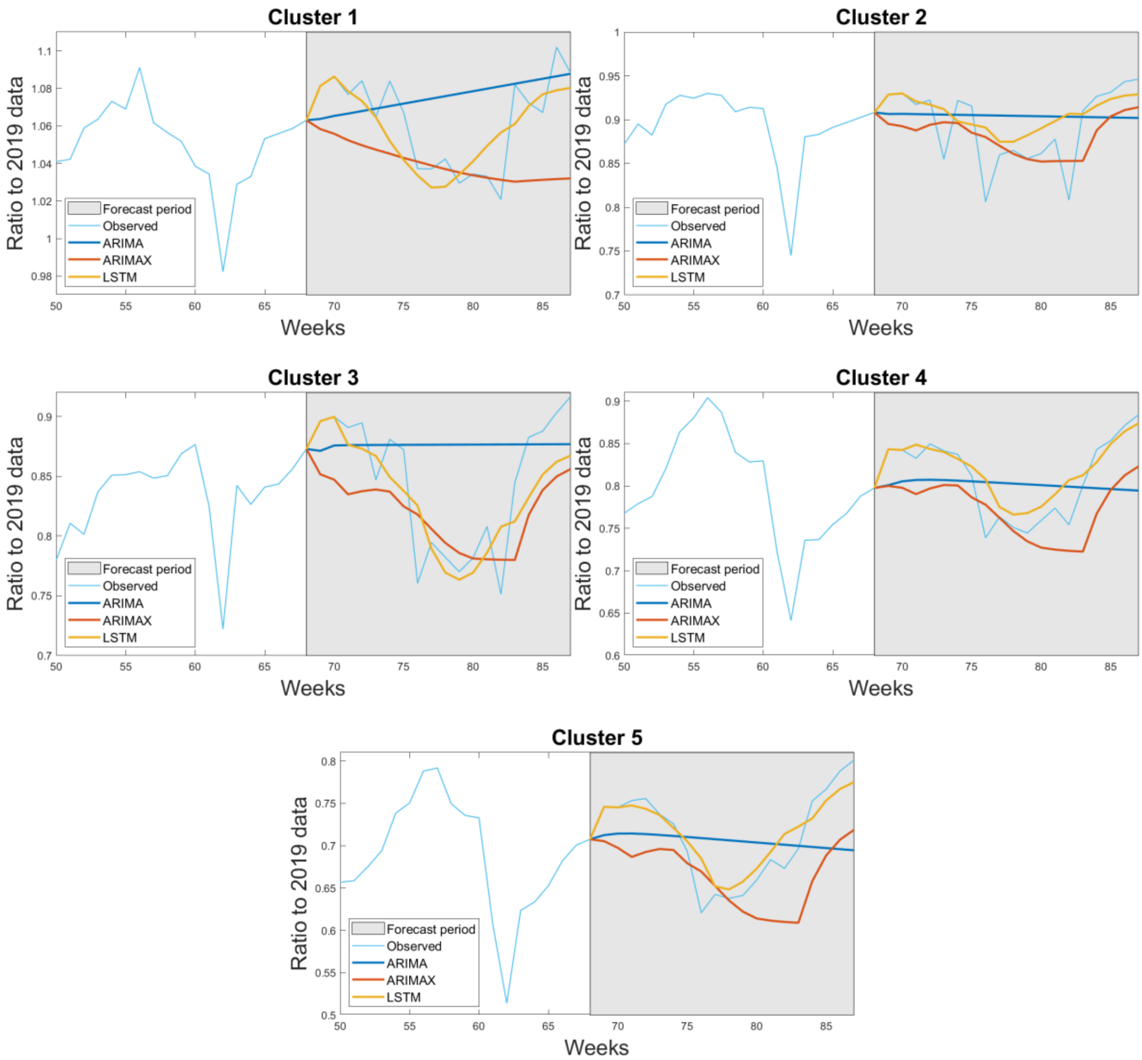

Figure 6.10 All clusters with 80% Training

6.2.3 Conclusions

In this Chapter, we evaluated different long-term forecasting methods for predicting post-pandemic public transportation usage, specifically focusing on the ARIMAX and LSTM models. Each method has its strengths and is suited to different scenarios, which is crucial for understanding station vitality recovery.

The ARIMAX model incorporates external variables such as COVID-19 cases and policy measures to enhance its predictive accuracy. The results show that ARIMAX is particularly effective for stations where external factors like new cases and policy restrictions heavily influence demand. The model's ability to include exogenous variables makes it suitable for capturing the direct impact of these external factors on station vitality. It performed best with an 80% training set, providing a balance between overfitting and predictive accuracy. This method is recommended for short-term forecasting where the effects of external variables are pronounced and can be accurately measured.

The LSTM model excels in capturing complex, non-linear demand patterns over longer periods. However, it requires substantial training data to achieve high predictive accuracy. The model's strength lies in its ability to handle long-term dependencies, making it suitable for forecasting in environments with highly variable and continuous demand patterns. It also performed best with an 80% training set, indicating its need for extensive data to accurately predict future demand. It is ideal for long-term forecasting where demand patterns are influenced by a variety of factors over time and require sophisticated modeling of these relationships.

This comparative analysis underscores the need for flexible and dynamic forecasting methods to navigate the complexities of public transportation demand during and after pandemics. By leveraging the strengths of both ARIMAX and LSTM models, public transport operators can enhance their strategic planning and operational efficiency, ensuring resilience and sustainability in the face of ongoing and future disruptions.

Chapter 7 Service-level reduction during a pandemic: a theoretical trade-off model

7.1 Introduction of a theoretical model

How to financially survive during a pandemic is a crucial question posed by COVID-19 to many businesses that lose demand due to the restrictions. For public transportation operators, fare-increases and cost-cutting by providing less service are two tools, but these become double-edged swords in the context. Increasing fares can boost revenues, but it may cause price-sensitive passengers to reconsider their usage and invite criticisms of "incompetence." Conversely, reducing frequencies can lower expenses, but a decrease in service quality may drive passengers to switch to other modes of transport. Additionally, safety and cleanliness are vital factors that involve operational constraints.

Building on this context, this chapter synthesizes insights from the previous chapters to develop a theoretical model for balancing service quality and operational constraints during a pandemic. This model considers financial resources, service levels, and the timing of service changes. We consider the service frequency as an easy target for potential cost reductions as it directly relates to variable, operational costs. However, we note that “frequency” in our model could also stand for other service quality related attributes that an operator might change. The change to cut operational cots involves two main decision variables: the new (reduced) frequency of the service and the timing of the frequency adjustments. Both are important as it affects passenger confidence in public transport. Premature reductions in service frequency may erode trust and cause passengers to switch to other modes of transport in the long term. On the contrary, timely adjustment of service frequency in response to improved public health conditions and recovery of demand can help retain passengers and restore confidence. In addition, the longer the epidemic lasts or the longer service frequency is reduced, the more likely it is that people will develop new habits and may permanently change their mode of travel. Such decisions will be partly based on knowledge of demand sensitivity to service frequency reduction as well as predictions as to how fast the demand will recover. An assumed rough knowledge of the latter we take from the findings from previous chapters.

By applying this theoretical model, we aim to explore how different decision-making approaches can lead to various outcomes under different impact scenarios. For instance, a decision to reduce service frequency early in the pandemic may have long-term repercussions on passenger retention and revenue. Conversely, maintaining high service levels incurs higher costs but could stabilize demand in the long term.

Through case studies based on a hereafter proposed theoretical model, this chapter demonstrates the potential consequences of different decisions made by public transport operators during a pandemic. It discusses the pros and cons of various strategies, ensuring that the balance between cost-effectiveness and demand retention is maintained. This analysis provides hence some insights for public transport operators to navigate the complexities of pandemic management, while also respecting different operational approaches and strategic thinking. Notably, many transit operators have only recovered around 80% of pre-pandemic demand at this point in time (Smart Cities Dive, 2024), highlighting the importance of strategic planning during such crises.

7.2 Idea of a theoretical model

Suppose following scenario: At the onset of a crisis such as the COVID-19 pandemic, public transportation (PT) operators face immediate and significant challenges. The fear of demand loss looms large as ridership plummets due to lockdowns, social distancing measures, and public fear of contagion. Operators must navigate short-term impacts on ridership while considering the long-term implications for demand and financial sustainability. We consider three core issues:

1) Operational constraints: these include financial limitations, workforce availability, and health regulations. Reduced revenues due to decreased ridership and increased costs associated with enhanced cleaning and safety measures exacerbate financial strain, limiting the ability to maintain high service levels.

2) Service level: maintaining a certain level of service is crucial to retaining passenger demand. Higher service quality can stabilize long-term demand but incurs higher operational costs.

Conversely, lowering service quality reduces costs but risks a decline in future demand. Operators must find the optimal balance to ensure both immediate and future sustainability.

3) Passenger demand: Understanding patterns of change in station vitality, influenced by factors such as passenger flow, commercial activity, and overall functionality, is critical. Accurate demand forecasting can help operators anticipate changes and adjust services proactively.

The variables are chosen below because they represent the fundamental trade-offs that public transportation operators must navigate during a crisis like the COVID-19 pandemic. Considering the multiple factors associated with operations during an epidemic, the variables and parameters included in this chapter are shown in Table 7.1, followed by a detailed explanation.

Table 7.1: Variables and parameters

Variables	**Expression**	**Unit**
Working variables and decision variables		
d	"Day" or "epoch" in the period of interest	*day*
$f(d)$	Frequency on day *d*	*services/day*
f_2	New service frequency; adjusted frequency due to pandemic impact	*services/day*
t_2	Frequency change time; the time at which the service frequency is adjusted	*day*
Input data, assumptions		
d_0	Starting date or "old normal"; the baseline date before the disruption/ pandemic	*day*
d_{end}	End date or "new normal"; the date when the system can be assumed to have stabilized after the pandemic/ disruption	*day*
t_s	Government declared start time of "state of emergency"	*day*
t_e	End time of "state of emergency"; emergency measures are lifted	*day*
$\mu(d)$	Passenger demand during the pandemic without any intervention by the operator	*passenger*

μ_0	Initial demand at d_0; abbreviation for $\mu(d_0)$	*pas*
f_1	Old, initial frequency before the pandemic	*services/day*
f_{min}	Minimum service frequency that must be provided at any time	*services/day*
μ_e	"Captive demand", minimum demand for essential needs, that is passengers that will use public transport even if only a minimum service is provided	*passenger*
μ_p	Demand during the peak pandemic; passengers that are willing to travel even at the peak at the pandemic	*passenger*
$\check{\mu}$	Minimum demand for essential needs at pandemic (lower than both μ_p and μ_e)	*passenger*
ξ	Financial resources "savings" at beginning of crisis	￥
F	Average fare per passenger	￥*/passenger*
E	Average expenses for the service per kilometer	￥*/kilometer*
l	Average distance per service journey	*kilometer*
c	Passenger capacity	*passenger*
β_p	Sensitivity of time in state of emergency, $t_e - t_s$	/
β_f	Sensitivity of f_2	/
β_r	Sensitivity of r	/
Derived variables		
K	Final demand $\tilde{\mu}(d_{end})$ at the end of the pandemic period (the "new normal")	*passenger*
$\tilde{\mu}(d)$	Passenger demand during the pandemic considering the response of the service operator	*passenger*
$r(d)$	the recovery speed of demand	/
FE	Ratio of Fare to Expense	%
Y	Total expected profit over the analysis period from d_0 to d_n in present value	￥
y_d	Profit on day d	￥

Working variables like the day d and service frequency $f(d), f_2$ help track and adjust the operational metrics over time. Input data and assumptions like initial demand μ_0, minimum service frequency f_{min} and financial resources ξ provide the baseline conditions and constraints, essential for realistic modeling. Derived variables such as the final demand K and recovery speed $r(d)$ offer insights into the outcomes of different scenarios, helping to optimize decision-making.

7.2.1 Decision variables

In developing a theoretical model for public transportation operations during a pandemic, several variables can be considered. These include fare adjustments, service frequency changes, operational costs, safety measures, and the timing of implementing these changes. The model is focused on two key decision variables: Service frequency and the timing of changes to this frequency.

1) New Frequency (f_2):

   Adjusting service frequency is a direct lever for controlling operational costs. During a pandemic, reducing the frequency of public transportation services can significantly cut expenses related to fuel, maintenance, and labor. However, a reduction in service frequency can also have a detrimental effect on passenger satisfaction and long-term demand. Passengers may switch to alternative modes of transportation if they perceive the service to be unreliable or insufficient, leading to a permanent loss in ridership. Hence, finding the optimal frequency that balances cost-saving with service quality is crucial. Here we labelled the new frequency as f_2 and correspondingly f_1 denotes the old frequency.

2) Timing of Change (t_2):

   The timing of when to implement changes in service frequency is equally important. Making changes too early in the pandemic might save costs immediately but could lead to a long-term decline in ridership as passengers adjust to alternative transportation modes. Conversely, delaying changes might maintain passenger trust and demand but at the expense of higher operational costs. Therefore, strategically timing the implementation of frequency changes can help mitigate the negative impacts on long-term demand while managing financial constraints. Note that the labelling here as t_2 instead of t is to harmonize with the new frequency f_2. No t or t_1 exists in the model.

With this we obtain frequency for each day:

$$f(d) = \begin{cases} f_1 & 0 < d < t_2 \\ f_2 & d \geq t_2 \end{cases} \tag{7.1}$$

7.2.2 Function of new maximum demand

A critical aspect to consider in the theoretical model is the maximum demand in the new normal, denoted as K. This variable represents the highest level of passenger demand that can be realistically expected once the pandemic has stabilized and society has adjusted to new norms of behavior and transportation. Understanding and estimating K is crucial for several reasons:

Firstly, K serves as a benchmark for planning service frequency and capacity. By knowing the potential upper limit of demand, operators can better tailor their services to meet actual needs without overcommitting resources. Secondly, accurate estimation of K allows for more precise financial projections. It helps in anticipating revenue flows and aligning them with operational costs, ensuring that the service remains financially viable in the long run. Thirdly, with a clear understanding of the maximum demand, operators can allocate resources more efficiently. This includes not only scheduling and staffing but also infrastructure investments and maintenance priorities. Lastly, providing services that align with K can enhance passenger confidence in the reliability and adequacy of public transportation. This is particularly important in the post-pandemic recovery phase, where rebuilding trust is essential.

Two main factors influencing K are assumed to be the new frequency and the duration of the emergency state. The new frequency affects passengers' willingness to continue using the service. Higher frequency generally leads to greater satisfaction and retention of passengers. Furthermore, the duration of the emergency state $(t_e - t_s)$ impacts passengers' confidence in the stability and reliability of the service. We do not consider t_2 in K as it has a more significant impact on operators rather than passengers. Passengers are less concerned with the exact timing of service changes and more with the extent of those changes. Incorporating K into the model helps to obtain realistic projections of future demand, ensuring that strategies are both effective and sustainable.

We need to ensure that K satisfies the following constraints:

- Condition 1: When the frequency remains the same and there is no pandemic, K equals the original demand μ_0

$$\lim_{\substack{f_2 \to f_1 \\ t_e - t_s \to 0}} K = \mu_0 \tag{7.2}$$

- Condition 2: When the frequency remains the same during a prolonged pandemic, K equals to the demand during the pandemic denoted as μ_p

$$\lim_{\substack{f_2 \to f_1 \\ t_e - t_s \to \infty}} K = \mu_p \tag{7.3}$$

- Condition 3: When the frequency f_2 decreases but there is no pandemic, K is determined by a smoothed function of the ratio between f_1 and f_2. The lower f_2, the lower the new demand and Eq. 7.3 is one equation fulfilling this. We note that we presume some low level of service must be maintained and we refer to this as f_{min}. If only this level of service is operated, then also only the "essential demand" that is captive to this service will remain and it is called μ_e.

$$\lim_{\substack{f_2 \to f_{min} \\ t_e - t_s \to 0}} K = \mu_0 \left[1 - \left(\frac{f_1 - f_2}{f_1}\right)^{\beta_f}\right] \to \mu_e \tag{7.4}$$

- Condition 4: When the frequency is at its minimum during a prolonged pandemic, K should not be lower than the demand that is captive and is still travelling during the pandemic. We refer to this minimum level of demand as $\check{\mu}$.

$$K \geq \check{\mu} \tag{7.5}$$

A function that fulfills these constraints is Eq. (7.6) as explained below.

$$K = \max\left\{\check{\mu}, \mu_0 - (\mu_0 - \mu_p)\left(1 - e^{-\beta_p (t_e - t_s)}\right) - \mu_0 \left(\frac{f_1 - f_2}{f_1}\right)^{\beta_f}\right\} \tag{7.6}$$

Explanations:

1) If $t_e \to t_s$ and $f_2 \to f_1$:

When $e^{-\beta_p(t_e - t_s)}$ approaches 1, the second term goes to zero. As $f_1 - f_2$ approaches 0, the third term also goes to zero. Therefore, K approximates μ_0, indicating no reduction in demand due to time and frequency change, resembling the conditions of the old normal. This confirms that Condition 1 is fulfilled.

2) If $f_2 \to f_1$ and $t_e \to \infty$

When $e^{-\beta_p(t_e - t_s)}$ approaches 0, the second term simplifies to $\mu_0 - \mu_p$. As $f_1 - f_2$ approaches 0, the third term also approaches zero. Therefore, K approximates μ_p, indicating that demand is reduced to the minimum level due to the prolonged pandemic, reflecting only essential demand. This confirms that Condition 2 is fulfilled.

3) If $t_e \to t_s$

When $e^{-\beta_p(t_e - t_s)}$ approaches 1, the second term goes to zero. Therefore, K approximates $\mu_0\left[1 - \left(\frac{f_1 - f_2}{f_1}\right)^{\beta_f}\right]$, indicating no reduction in demand due to time, only determined by f_2. Condition 3 is fulfilled.

4) If $f_2 \to f_{min}$ and $t_e \to \infty$

The term $e^{-\beta_p(t_e - t_s)}$ approaches 0, the second term goes to zero. Therefore, K approximates $\mu_p - \mu_0\left(\frac{f_1 - f_2}{f_1}\right)^{\beta_f}$. The function needs to ensure that K is non-negative, thus $\max\left\{\check{\mu}, \mu_0 - (\mu_0 - \mu_p)\left(1 - e^{-\beta_p(t_e - t_s)}\right) - \mu_0\left(\frac{f_1 - f_2}{f_1}\right)^{\beta_f}\right\}$ ensures demand does not drop below zero, maintaining non-negativity. Condition 4 is also fulfilled.

5) β_p

When f_2 remains the same, β_p determines the speed at which demand drops as $t_e - t_s$ increases. A large β_p means demand drops more quickly from μ_0 to μ_p. The value of β_p depends on the fact that when $t_e - t_s$ is 49 days (the actual control period), the K value of the group just happens to hit the lowest value μ_p in the pandemic. We found that when β_p is 0.09, it is more suitable for all clusters.

6) β_f

Conversely, when $t_e \rightarrow t_s$ remains the same, β_f determines the rate at which demand grows as f_2 increases. A large β_f means demand grows more quickly from the demand at lowest f_2 to reach μ_0. The value of β_f depends on the maximum capacity when the frequency is increased, i.e. the increase in the case of overload. On the basis of the currently generally accepted overload ratio of 20%, we have calculated that at a β_f of 1.2, the demand will not exceed the maximum capacity at all frequencies.

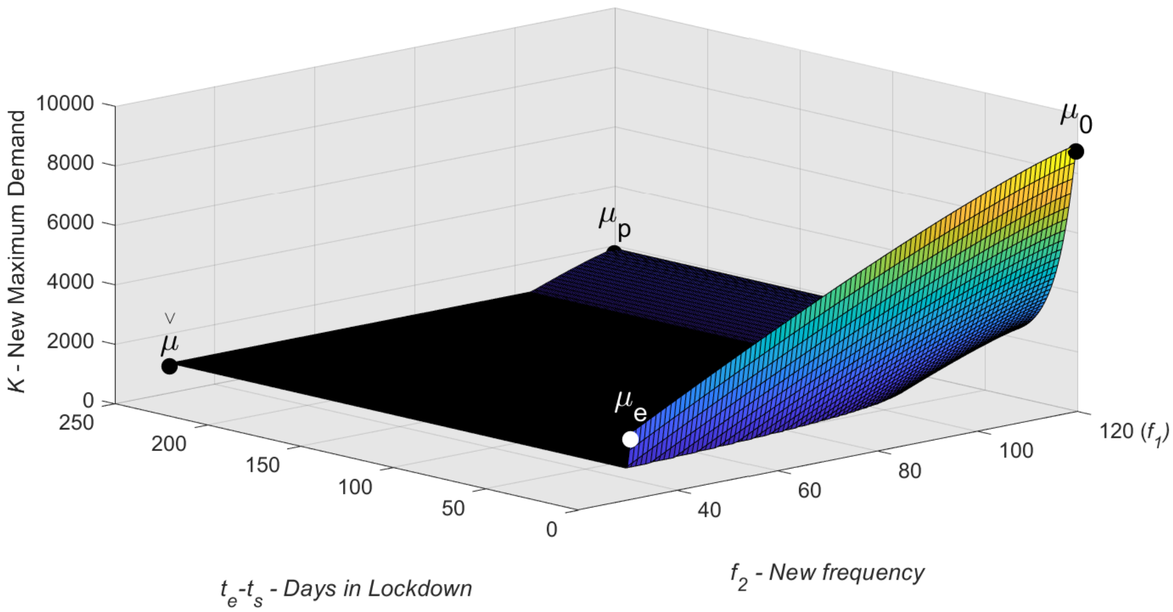

Figure 7.1(a) An example of K of Cluster 5 (parameter settings are the same as in Table 7.2)

It can be seen that K in Fig. 7.1(a) conforms better to the above four limits. Next, we will use the obtained new demand values for a case study.

Once we have determined K under the specified conditions, it is equally important to understand the rate at which this demand recovers, represented by r. r calculates the immediate demand when the new frequency f_2 is introduced. This rate of recovery is crucial because it indicates how quickly the demand approaches its maximum potential after service adjustments. It helps to quantify the demand response to the new service frequency, guiding operators in optimizing their strategies during the recovery phase.

Furthermore, if K exceeds the upper capacity limit that f can provide, the actual recovered demand will be constrained by this upper capacity limit. In other words, even if there is a higher potential demand, the service can only accommodate up to its maximum capacity. This limitation must be accounted for in planning and forecasting to avoid overestimating the system's ability to recover and meet passenger needs.

From $r(d)$, we know $\mu(d)$ would finally reach cf_2 or K, the smaller one

$$r(d) = \beta_r \left(1 - \frac{\tilde{\mu}(d-1)}{\max(cf_2, K)}\right)\left(1 - \frac{f_1 - f_2}{f_1}\right)^{\beta_f} \tag{7.7}$$

The value of β_r is determined by both the observed and calculated values of the recovery period. When f_2 is equal to f_1 and $t_e - t_s$ is equal to the actual control duration, the calculated value $\tilde{\mu}(d)$ should be as close as possible to the observed value $\mu(d)$. Since all f_2 values are less than or equal to f_1, the calculated value should be slightly smaller than the observed value, as shown in Fig 7.1(b). Additionally, the value of f_2 also affects the recovery speed - the smaller the f_2 value, the slower the recovery speed. Furthermore, the value of β_r is also carefully fine-tuned to ensure consistency with the long-term forecasts developed in Chapter 6. This calibration helps to integrate the observed recovery trends with the model's predictions, validating the overall approach by aligning it with the broader forecasting framework.

With this we recursively obtain demand for each day

$$\tilde{\mu}(d) = \begin{cases} \mu(d) & 0 < d < t_2 \\ \min\big(\mu(d), \tilde{\mu}(d-1)(1 + r(d)), cf_2\big) & d \geq t_2 \end{cases} \tag{7.8}$$

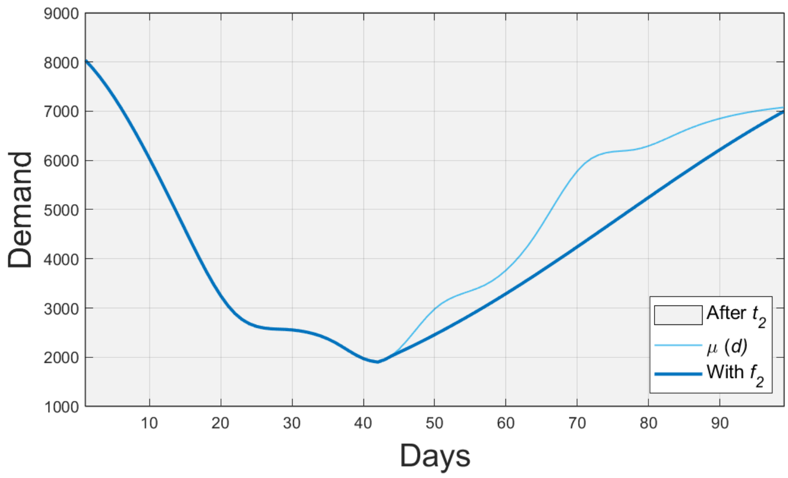

Figure 7.1(b) An example of $\tilde{\mu}(d)$ fitting $\mu(d)$ of Cluster 5 ($\beta_r = 0.042$)

7.2.3 Objective function

The theoretical model aims to balance these considerations by optimizing service frequency and timing to maximize long-term demand while minimizing operational costs. The model must adhere to constraints such as limited financial resources and the necessity of providing a minimum level of service at all times.

The goals of the operator is to maximize outcome Y, which is the total profit during the pandemic period from the start day d_0 until the day of a new normal d_{end} while applying a potentially different f_2 (new frequency) and t_2 (frequency change time).

$$\max_{f_2 t_2} Y = \sum_{d_0}^{d_{end}} \mu(d)F - f(d)El \tag{7.9}$$

The timing of the frequency change t_2 can be earlier or later than the state of emergency start time t_s, depending on the operator's decision. $t_2 < t_s$ would indicate that the operator anticipates a large impact from the first signs of the onset of the pandemic and wants to react earlier. In contrast, $t_2 > t_e$ likely indicates that the operator is forced to react. The demand is already recovering, however, financial constraints mean keeping the service at its old level is not any more sustainable.

$$d_0 < t_2 < d_{end} \tag{7.10}$$

$$d_0 < t_s < t_e < d_{end} \tag{7.11}$$

The new frequency f_2 could be larger or smaller than f_1, however, in general we expect a reduction in frequency. It should further be larger than f_{min}, a minimum frequency that the operator might be obliged to provide due to regulations from the regulator.

$$f_{min} \leq f_2 \tag{7.12}$$

Clearly, a lower frequency means that also the capacity is reduced, which might hence lead to not all demand being served which is expressed with (7.13).

$$\tilde{\mu}(d) \leftarrow \min(\tilde{\mu}(d), f(d)c) \tag{7.13}$$

A company must have sufficient financial resources to keep the service running any following day. This is described in (7.14) where ξ are the savings (or government subsidy), the sum term describes the profits minus expenses for all previous days, and the last term denotes the expenses for the next day.

$$0 < \xi + \sum_{d=d_0}^{d_{end}-1} y_d + f(d)El \quad \forall\, d \tag{7.14}$$

7.3 Case study

This section presents a case study applying the theoretical model to a major Japanese railway station, exploring the trade-offs between service quality, operational constraints, and long-term demand during the COVID-19 pandemic. The vitality of a railway station is directly linked to the rail demand for a line because higher demand ensures consistent usage and activity at the station, which in turn supports its economic and operational viability. Since it is difficult to calculate the cost per kilometer for railways due to the complexity and variability of rail operations, we use data from the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) for buses as a proxy. Specifically, the line frequency and length are based on data from the Kyoto city bus system. This approach allows us to approximate operational costs and assess the trade-offs in a more manageable way, while acknowledging the limitations of this substitution. Although bus operations differ from rail, this method provides a practical solution to estimate costs and informs our analysis of service adjustments.

7.3.1 *Input variables*

The case study is based on the data and scenarios provided in Table 7.1, which outlines various service adjustment scenarios and their expected impacts. Additionally, Table 7.2 details the input variables used in this case study, providing a comprehensive overview of the parameters influencing the analysis.

Table 7.2: Input variables

Operation input			
Pandemic related and according to assumptions		**Operational scenario**	
Variables	**Value**	**Variables**	**Value**
$\mu(d)$	MSS data in first wave	f_1	120
μ_p	Minimum of $\mu(d)$	f_{min}	30
$\check{\mu}$	50% of μ_p	c per service	80
t_s	30	l	8
t_e	60	F	30 to 570 in steps of 10
d_{end}	99	E	600
β_p	0.09	ξ	Scenario specific
β_f	1.2		
β_r	0.042		

Explanations:

β_p, Sensitivity of demand to the duration of the pandemic, a larger β_1 indicates a faster decline in demand when duration is getting longer.

β_f Sensitivity of demand to changes in service frequency, A larger β_2 implies a quicker recovery in demand when new frequency is getting larger

β_r Sensitivity of recovery speed, A larger β_r implies a quicker recovery in demand

E Cost per kilometer per service (data from the MLIT for buses)

F We go from 5% to 95% of the kilometer cost in steps of 10 (10 is a common step for fares)

f_1 Assuming 15 hours of operation per day and 4 services per hour in each direction, the total number of services per day in both directions is 120

c The maximum capacity of a large vehicle is about 75 per service, rounded to 80 (this data is also from buses)

l	Assuming an average distance of 8 kilometers for each service
μ_p	From the MSS data in Chapter 4, we reached μ_p (demand in pandemic) at day 42
$\breve{\mu}$	We set $\breve{\mu}$ 50% of μ_p as the essential demand
d_{end}	From the MSS data in Chapter 4, it can be seen that it took about 14 weeks from the start of the significant reduction in demand to recover to the first steady state
$t_e - t_s$	From Table 6.3, we can see that the average duration of the first lockdown is between 1 and 1.5 months (all of Japan), and we set it at 30 days for ease of understanding.
f_{min}	Reduction to 1 quarter of the original service frequency, i.e., one service per hour in one direction

7.3.2 *Result of f_2 and t_2 for each cluster*

Cluster 5:

We perform this calculation starting with Cluster 5 and get the result shown in Figures 7.2 and 7.3. In Fig. 7.2, the blue solid line represents the operator's maximum profit Y at different fares (FE), which corresponds to the y-axis on the left side; the red solid line represents the frequency of the new service at the time when the maximum profit is achieved, and the yellow dotted line represents the point in time when the frequency of the change is made at this time, and both of them correspond to the y-axis on the right side.

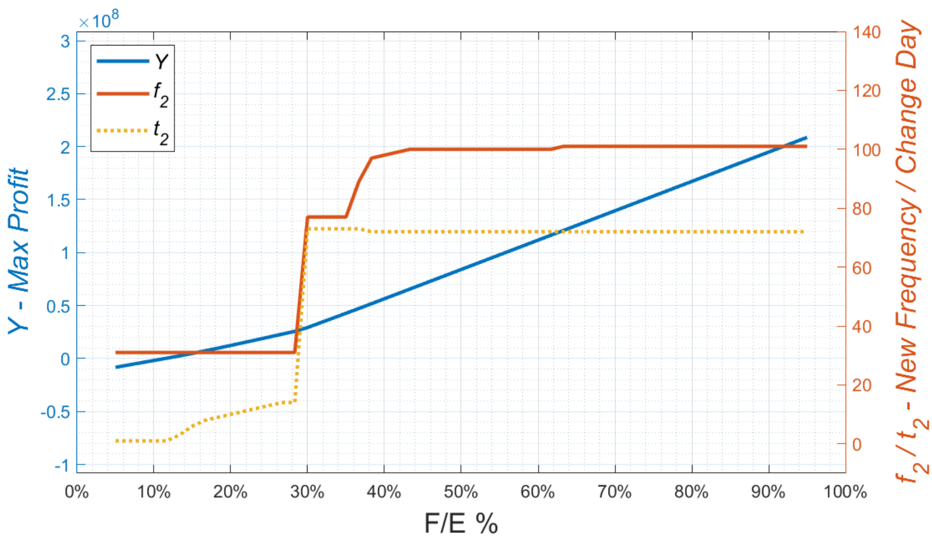

Figure 7.2 Maximum profit, f_2 and t_2 of every FE of Cluster 5 (sufficient savings, i.e. large ξ)

It can be seen that the maximum profit increases with the increase in ticket price, and the corresponding service frequency does not continue to increase after reaching about 100 (about 83% of the original frequency), which shows that due to the decrease in demand caused by the pandemic, maintaining the original service frequency will result in losses. The optimal time to change frequency is the first day when the FE is below 10 percent, gradually postponing from the first day to about the 20th day when the FE is between 10-30 percent, and stabilizing around the 70th day after 30 percent. This suggests that in the event of a pandemic, it is necessary for operators with lower fare revenues to adjust frequencies as soon as possible to avoid excessive losses during a period of declining demand, while 30% can be seen as a " base point " beyond which adjustments can continue to be delayed. New frequencies are not as low as possible, but need to be accurately matched to the growth in passenger demand at a later stage.

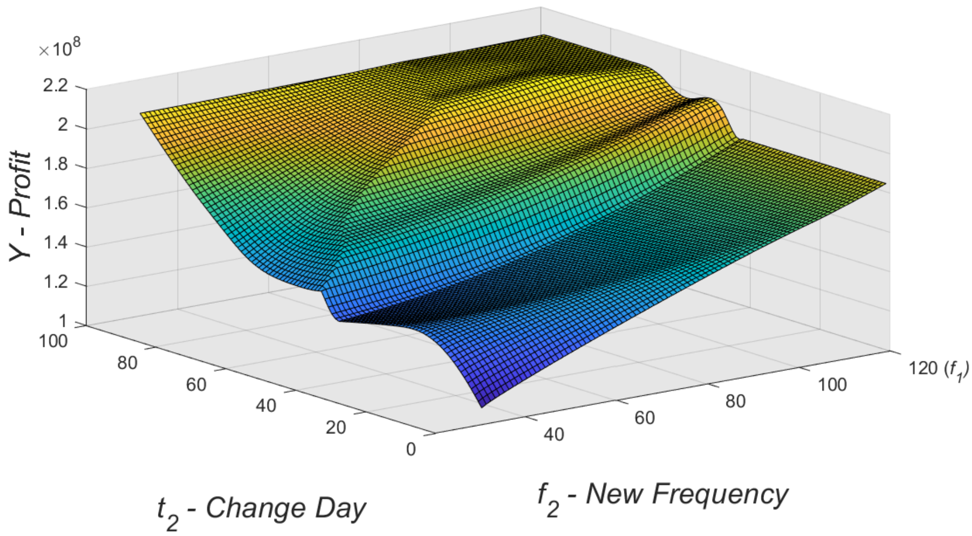

Figure 7.3 Profit of different combinations of f_2 and t_2 of Cluster 5 (FE 95%)

We take 95% FE as an example to explore the impact of different f_2 and t_2 on profit under the same FE. Under this FE, the maximum profit occurs when f_2 is 100 and t_2 is 72. However, as we can see from Fig. 7.3, there is a "plateau" with higher profit in the range of f_2 from 80 to 120 and t_2 from 72 to 99. This shows that as long as the new frequency is guaranteed to be above a certain point and the adjustment point is after a certain day, then the profit will not be very low. This also reflects the large impact on Cluster 5 demand, and increasing capacity by 1/2 (from 80 to 120) is still relatively not a big loss. For areas that are greatly affected, it is necessary to carefully assess the subsequent demand situation. In this case, it is not recommended to reduce the frequency by more than 1/3, and the adjustment frequency should be as early as possible.

We compare the demand before and after the adjustment. As shown in Fig. 7.4, the demand after the adjustment $\tilde{\mu}$ increases the same as before and finally reaches the previous demand level and remains there. As can be seen in Figure 7.2 (b), the recovery speed we preset is slower than the actual observed value, but the speed here is the same. This is because we preset the entire recovery process, and the actual recovery speed is less than the preset speed when it is more than 70 days. At this time, the optimal frequency of 100 is less than the original frequency and cannot be greater than the observed value, so it is taken as equal to the observed value. This phenomenon can be further optimized by taking different β_r values according to different recovery intervals. From this result, we can also judge that when the majority of the demand in the recovery period is met, appropriately reducing the frequency means that costs can be reduced and the impact of frequency adjustment minimized. In addition, as discussed earlier, we should choose a larger f_2 value within the scope of affordability, which will give us more flexibility in post-pandemic operations: we can meet the reduced demand while also having sufficient resources to attract new demand.

We apply the same method to other clusters to obtain the following results:

Cluster 4:

As can be seen in Fig. 7.5, compared to Cluster 5, the f_2 corresponding to the maximum profit of Cluster 4 rises to 106, while the "base point" shifts to the left from 30 to about 25 percent. This means that the "plateau" of high profits is smaller, but at the same time the gap between different combinations of f_2 and t_2 increases slightly, as shown in Fig. 7.6. Since the minimum demand for Cluster 4 is higher compared to Cluster 5, the frequency that can be guaranteed for the same fare is also higher, and there is also a brief stop at around 90 before it is raised to 106. In Fig. 7.7, the adjusted $\tilde{\mu}$ reaches a lower maximum demand after the pandemic.

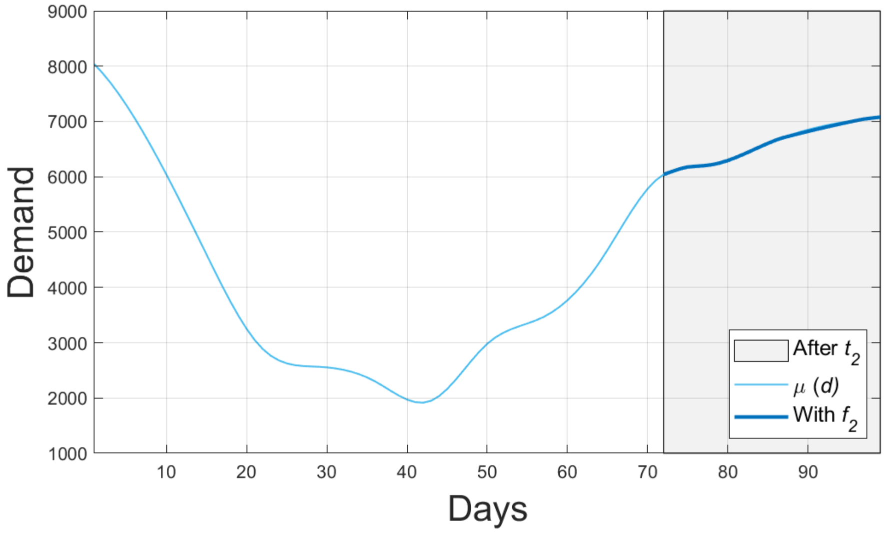

Figure 7.4 μ and $\tilde{\mu}$ of Cluster 5 when reaching maximum profit (FE 95%)

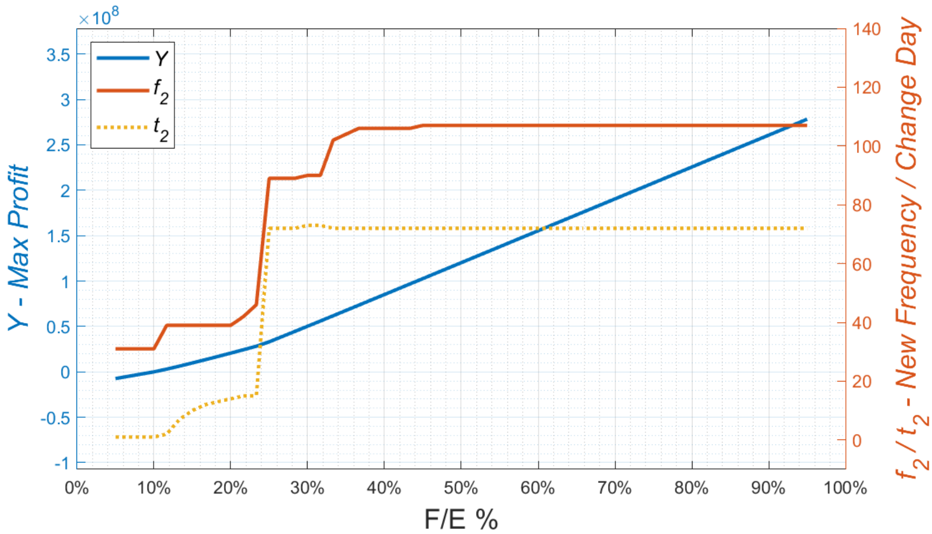

Figure 7.5 Maximum profit, f_2 and t_2 of every FE of Cluster 4 (sufficient savings, i.e. large ξ)

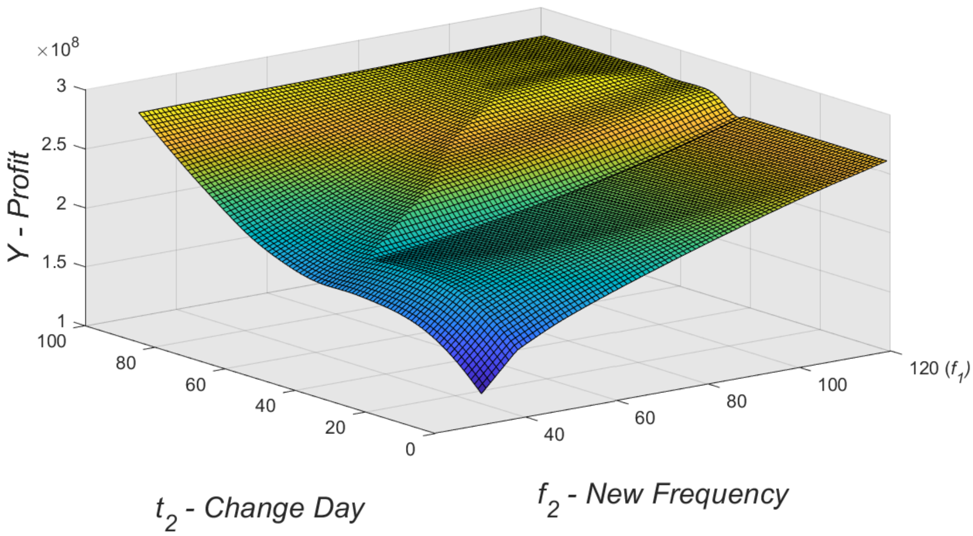

Figure 7.6 Profit of different combinations of f_2 and t_2 of Cluster 4 (FE 95%)

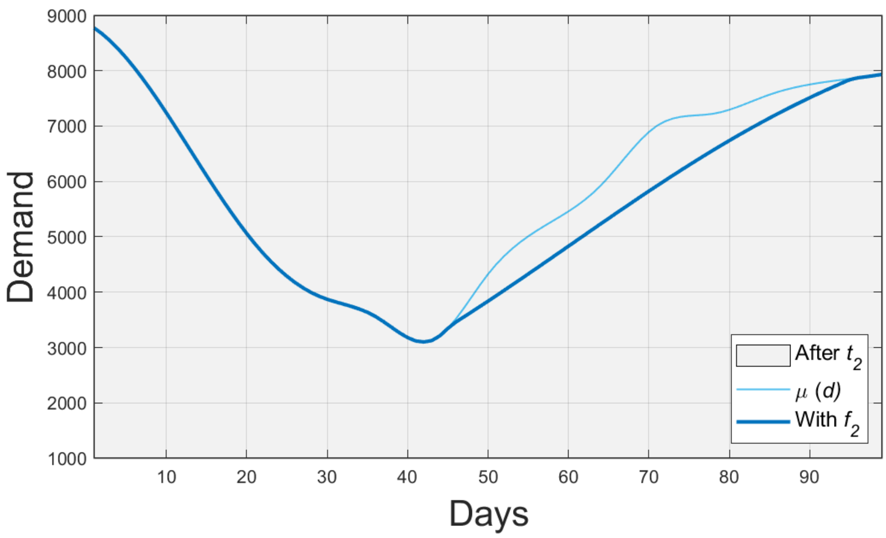

Figure 7.7 μ and $\tilde{\mu}$ fitting of Cluster 4 ($\beta_r = 0.042$)

Cluster 3:

As can be seen in Fig. 7.8, f_2 at the maximum profit point of Cluster 3 continues to rise to 116, while t_2 remains unchanged at one. The "plateau" in Fig. 7.9 is also narrowing further, and the gap between the profits of different t_2 at high f_2 is also decreasing. For Cluster 3, a FE of 30% is sufficient to support operation at the maximum frequency, while several fixed frequencies are raised before the maximum frequency is raised. The period of decline in Fig. 7.10 is almost a straight line, with a small increase in the rate of increase.

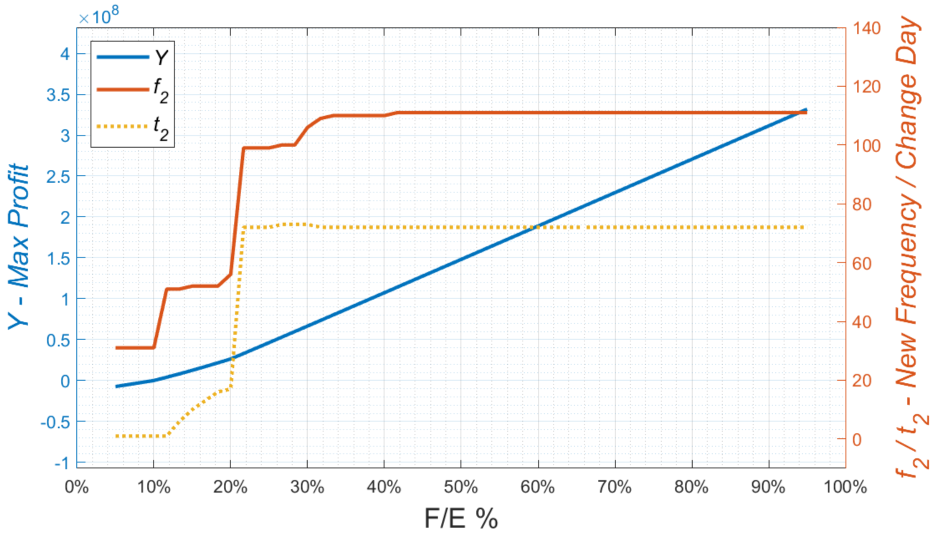

Figure 7.8 Maximum profit, f_2 and t_2 of every FE of Cluster 3 (sufficient savings, i.e. large ξ)

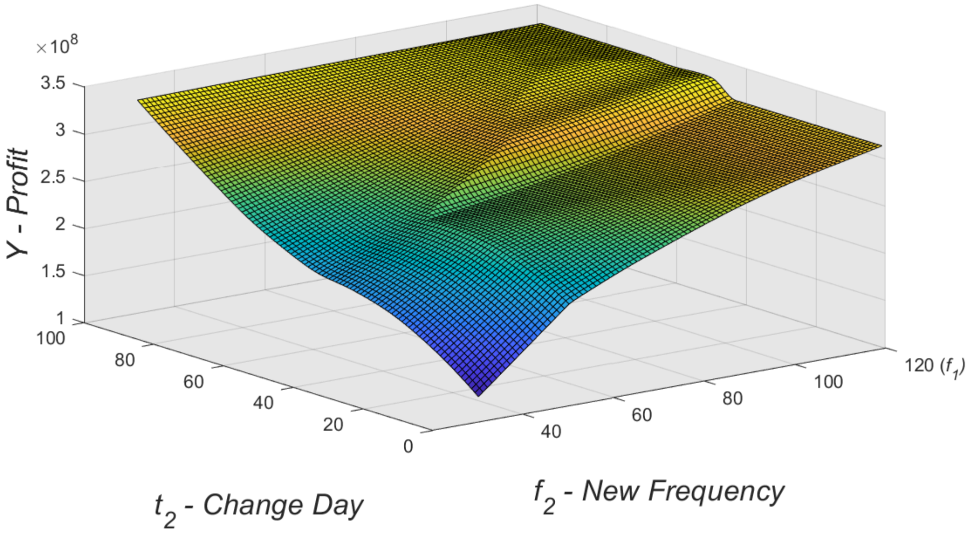

Figure 7.9 Profit of different combinations of f_2 and t_2 of Cluster 3 (FE 95%)

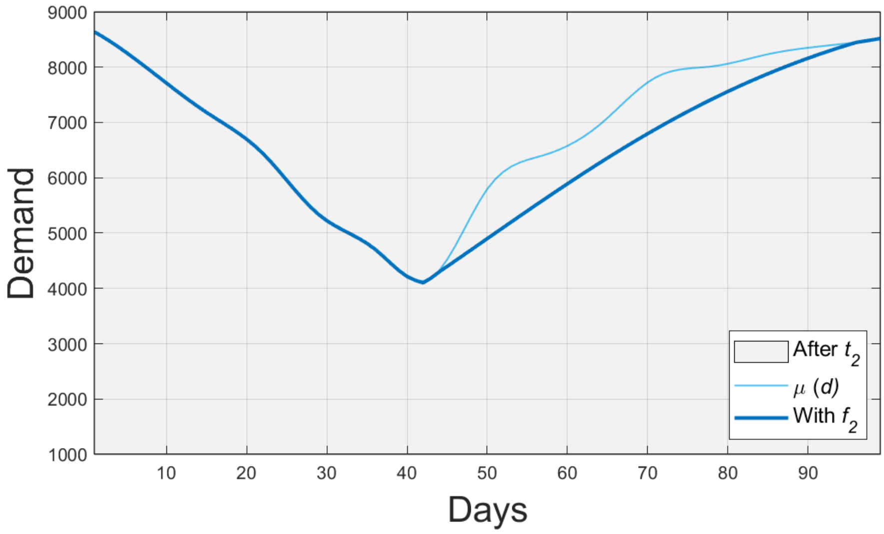

Figure 7.10 μ and $\tilde{\mu}$ fitting of Cluster 3 ($\beta_r = 0.042$)

Cluster 2:

As can be seen in Fig. 7.11, f_2 at the maximum profit point of Cluster 2 rises to 119, which is almost the same as the original frequency f_1. The timing of the frequency change is more complex: the optimum in the FE 20-25% interval is the same as the previous cluster, at around 70, while after 25% it drops to around 55. We can see in Fig. 7.13 that the observed values rise rapidly at days 42-52, with a gradual slowing of the subsequent rise. This suggests that meeting the needs of the "first wave of recovery" is more important compared to the later stages. The size of the "plateau" in Fig. 7.12 continues to decrease, but a larger plateau is forming. In Fig. 7.13, the demand minimum rises to 5000, with a slight decrease in the rate of increase.

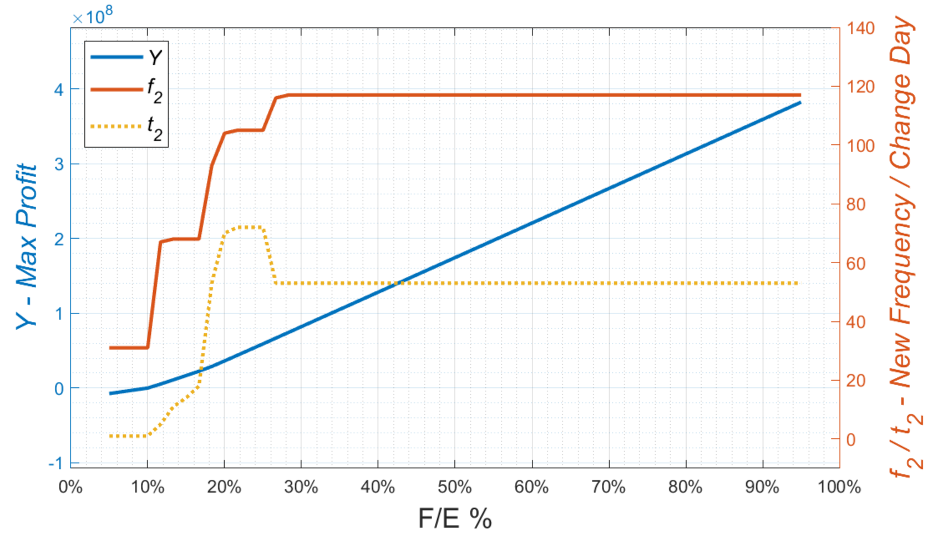

Figure 7.11 Maximum profit, f_2 and t_2 of every FE of Cluster 2 (sufficient savings, i.e. large ξ)

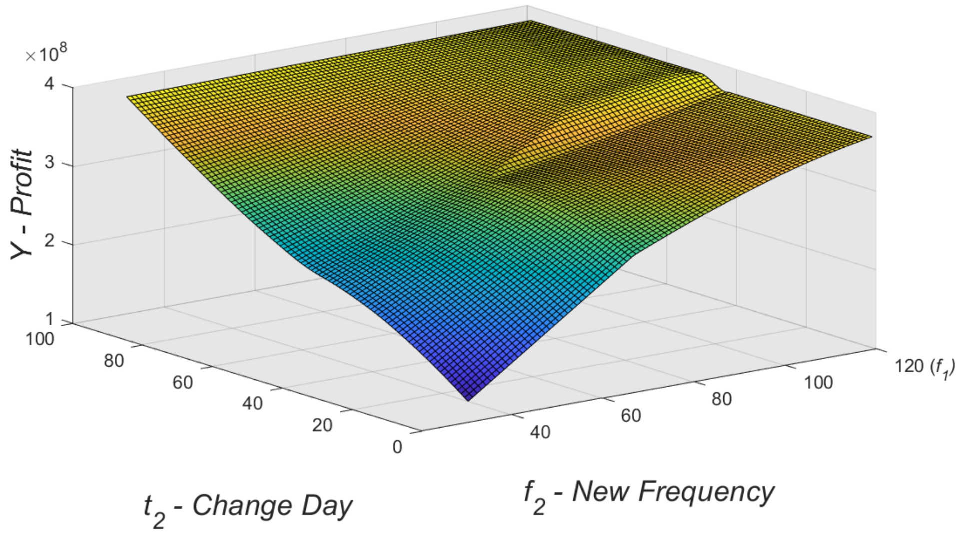

Figure 7.12 Profit of different combinations of f_2 and t_2 of Cluster 2 (FE 95%)

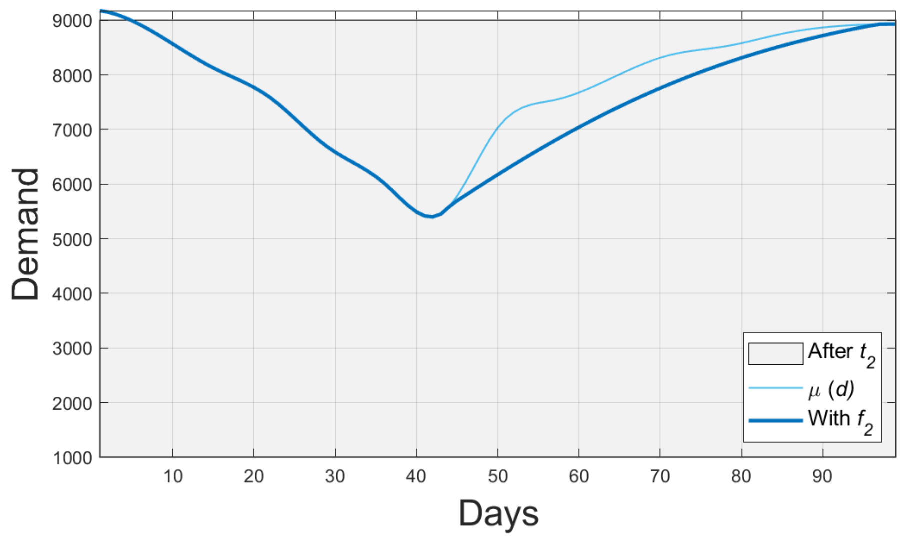

Figure 7.13 μ and $\tilde{\mu}$ fitting of Cluster 2 ($\beta_r = 0.042$)

Cluster 1:

As can be seen in Fig. 7.14, f_2 at the point of maximum profit for Cluster 1 is the same as the original frequency, f_1, and t_2 can take on any value in this case. The "plateau" in Fig. 7.15 essentially disappears and becomes a large "slope". In Fig. 7.16, the lowest point of the demand has been very close to the original demand, because the value of mu in the late period has been larger than the value before the epidemic, so $\tilde{\mu}$ has been smaller than μ.

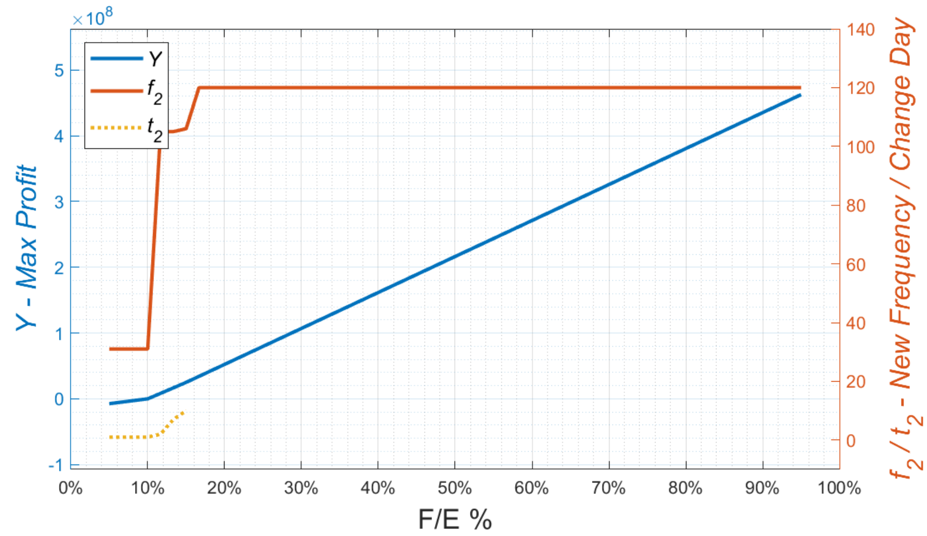

Figure 7.14 Maximum profit, f_2 and t_2 of every FE of Cluster 1 (sufficient savings, i.e. large ξ)

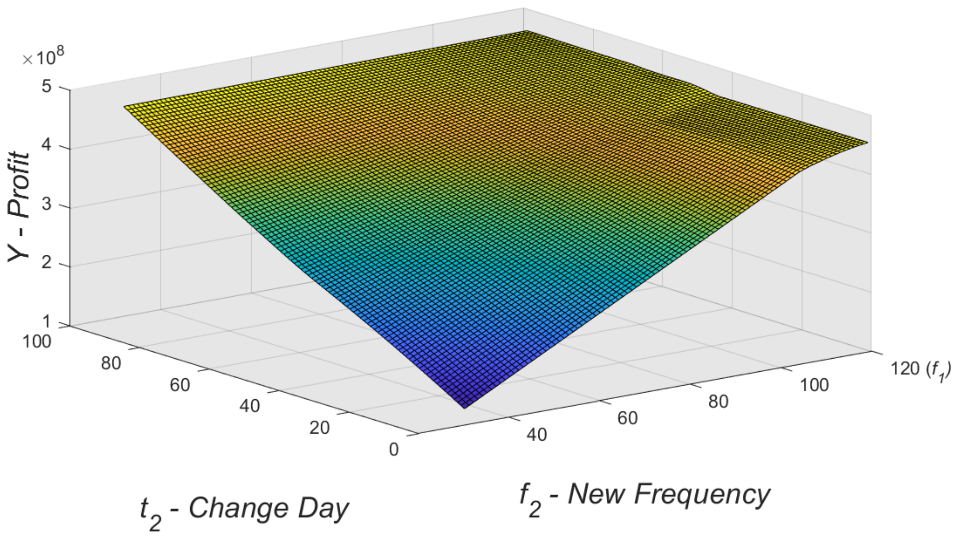

Figure 7.15 Profit of different combinations of f_2 and t_2 of Cluster 1 (FE 95%)

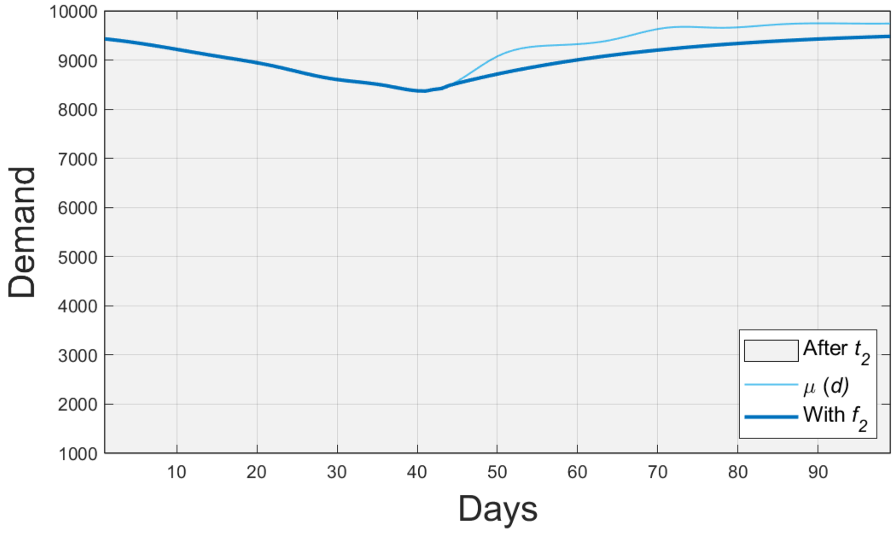

Figure 7.16 μ and $\tilde{\mu}$ fitting of Cluster 1 ($\beta_r = 0.042$)

7.3.3 Result of ξ for each cluster

Having sufficient savings at the onset of a pandemic is crucial. These financial reserves serve as a buffer to absorb initial losses and maintain operations during periods of reduced demand. By monitoring cumulative profit, operators can adjust strategies to optimize service levels and operational costs, balancing short-term and long-term demand while maintaining financial stability.

In the case study in Section 7.3.2, we assume that the public transport operator has sufficient savings to continue operating even if it incurs a loss. However, we also need to consider the actual situation, and when the loss reaches a certain level, or when the savings are exhausted, the operation will be suspended. So far, we have set the Eq. 7.14 as a constraint to ensure that the operator has sufficient funds to continue operating the next day. Since a direct solution is complicated, we calculate the lowest amount (which can be negative) on the balance for the entire process from the first day when the capital is assumed to be 0 to the last day, for any arbitrary set of f_2 and t_2. Since the operator does not necessarily choose the optimal f_2 and t_2 in previous section, the worst scenario needs to be considered. We take the absolute value of the lowest point in each financial scenario as the maximum initial savings required.

We record the minimum profit with its point in time. As can be seen from Table 7.3 and Fig. 7.17 for Cluster 5, where the minimum profit increases as the FE value increases, the lowest point is when the ticket price is only 30 yen, which is about minus 43 million yen. This also means that for such a line, at least the same amount of money would be needed to ensure that the operation is not in deficit. The “zero point” of the minimum profit appears around 25%, which is the date of the first day. This also means that for stations in Cluster 5, FE greater than 25% can guarantee that the operator can continue to operate without saving.

For Clusters 4 to 1, similar trends can be observed with varying financial reserve requirements and "zero points." In Cluster 4 (Fig. 7.18), the financial reserve requirement decreases to about 40 million yen, while the "zero point" shifts to approximately 20%. In Cluster 3 (Fig. 7.19), the decline in the financial reserve requirement slows, and the "zero point" moves to around 15%. For Cluster 2 (Fig. 7.20), the financial reserve requirement reduces to within 35 million yen, with the "zero point" slightly shifting to about 13%. Lastly, in Cluster 1 (Fig. 7.21), the financial reserve requirement decreases to less than 30 million yen, and the "zero point" shifts slightly to the left, remaining above 10%.

The requirement for financial savings by different clusters can be seen that the cluster with less demand loss can reach "zero point" faster when the FE value gradually increases. This also fully reflects the importance of reducing losses to maintain operations, and of course the price of tickets also plays a key role.

Table 7.3: Lowest cumulative profit and date

$\boldsymbol{FE}$ **- fare**	5%	10%	15%	20%	25%
$\boldsymbol{d}$ **- date**	d_{end}	d_{end}	81th	65th	60th
$-\boldsymbol{\xi}$ **- saving**	-43,170,000	-29,318,000	-16,139,000	-8,121,500	-1,116,200
$\boldsymbol{FE}$	30%	35%	40%	45%	50%
$\boldsymbol{d}$	d_0	d_0	d_0	d_0	d_0
$-\boldsymbol{\xi}$	870,430	1,111,500	1,352,600	1,593,600	1,834,700
$\boldsymbol{FE}$	55%	60%	65%	70%	75%
$\boldsymbol{d}$	d_0	d_0	d_0	d_0	d_0
$-\boldsymbol{\xi}$	2,075,800	2,316,900	2,557,900	2,799,000	3,040,100
$\boldsymbol{FE}$	80%	85%	90%	95%	
$\boldsymbol{d}$	d_0	d_0	d_0	d_0	
$-\boldsymbol{\xi}$	3,281,100	3,522,200	3,763,300	4,004,400	

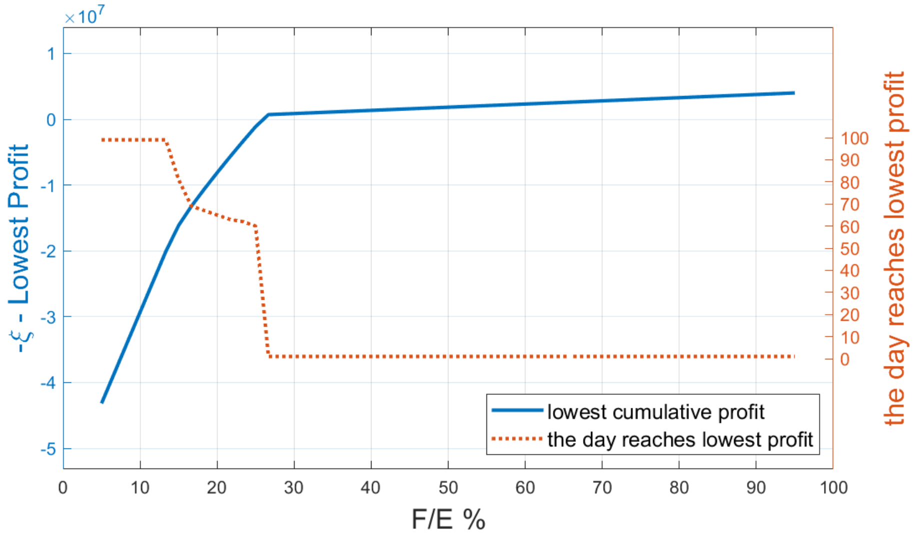

Figure 7.17 Lowest cumulative profit and date of Cluster 5

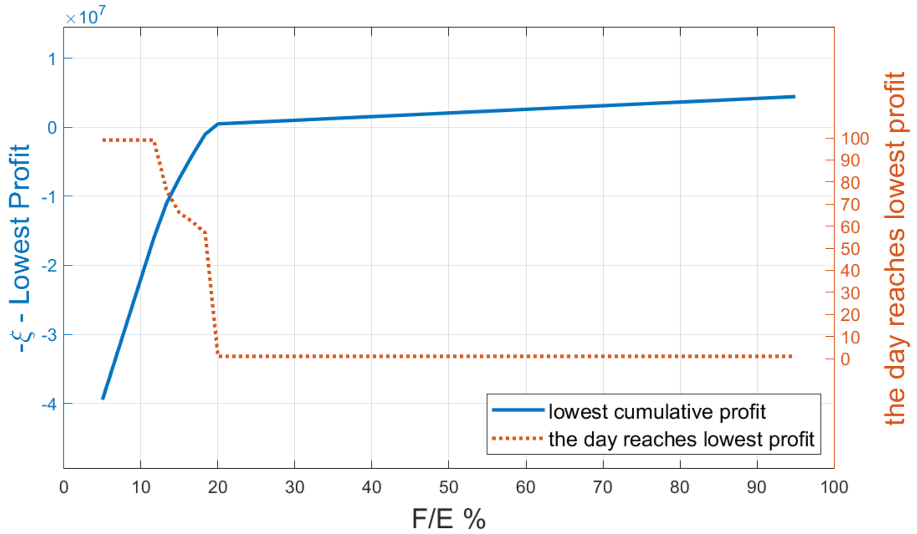

Figure 7.18 Lowest cumulative profit and date of Cluster 4

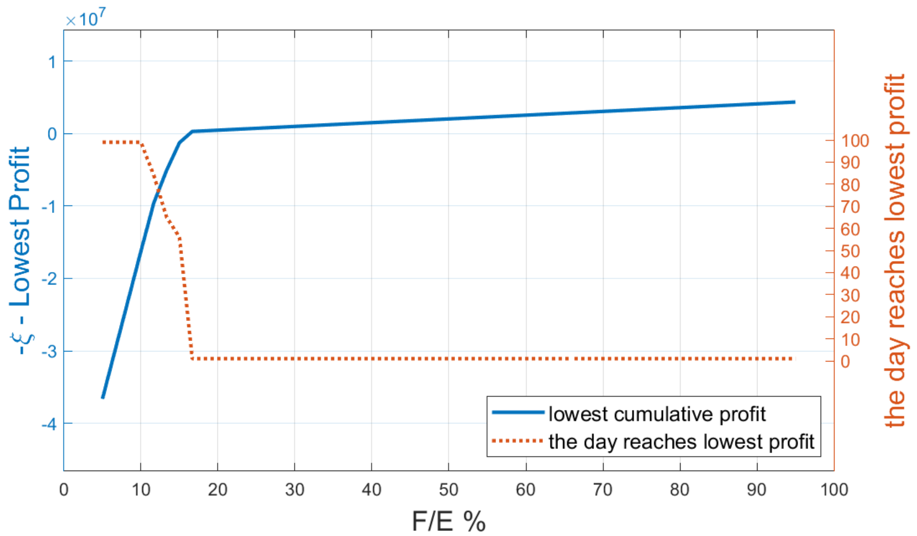

Figure 7.19 Lowest cumulative profit and date of Cluster 3

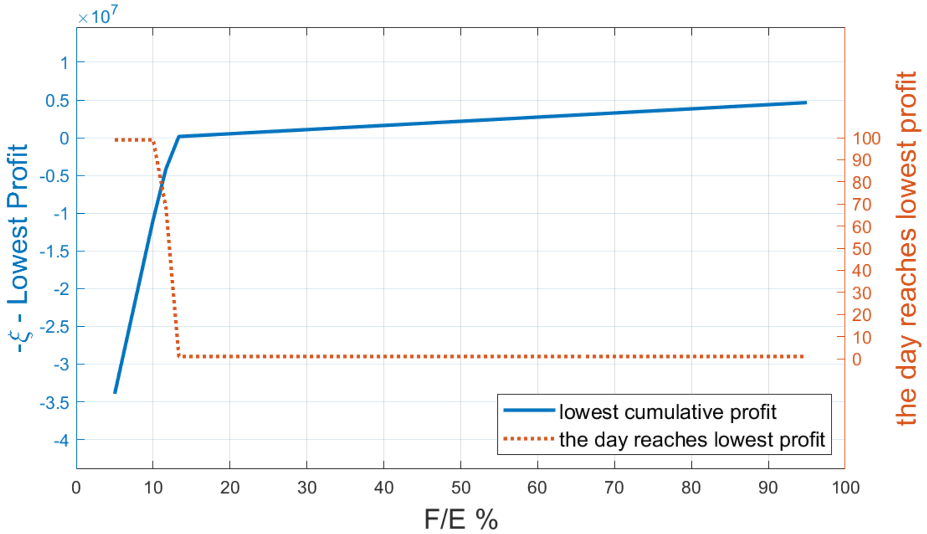

Figure 7.20 Lowest cumulative profit and date of Cluster 2

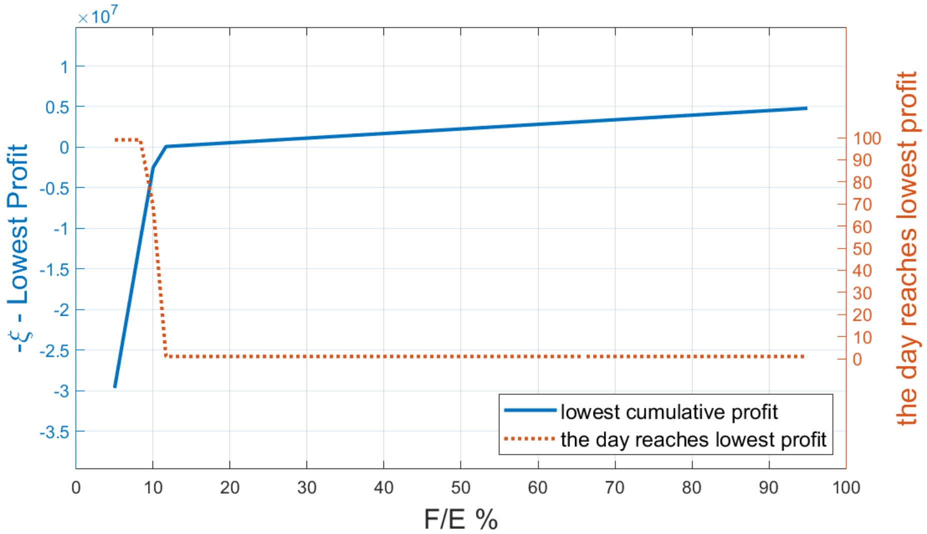

Figure 7.21 Lowest cumulative profit and date of Cluster 1

7.3.4 Conclusions

The trade-off analysis revealed that maintaining higher service levels was financially viable only when the revenue-to-expenditure ratio exceeded 30%. When the ratio was lower, immediate service reductions were necessary to mitigate financial losses. The analysis provides a clear framework for evaluating financial implications of different service levels.

Early implementation of service changes provided immediate financial relief but had varying impacts on long-term demand. Delayed adjustments allowed for better demand retention but incurred higher short-term costs. The findings emphasize the need for strategic timing in implementing service adjustments to maximize their effectiveness.

The case study demonstrates that public transport operators must carefully balance service quality and operational constraints to maintain long-term demand. High service quality, while costlier, can stabilize ridership and support recovery post-pandemic. However, financial viability must be assessed continuously, and adjustments should be made based on real-time data and evolving conditions.

By analyzing different scenarios for low- and high-quality services, this chapter illustrates how operating costs and future demand stability are affected. It provides practical insights for public transport operators to make informed decisions that balance cost-effectiveness and demand retention. Ensuring a resilient and sustainable public transportation system requires flexibility, continuous monitoring, and a strategic approach to balancing service quality and operational constraints.

Chapter 8 Conclusions

As discussed in the previous chapters, the COVID-19 pandemic has posed critical challenges to public transportation systems, particularly in Japan. The significant shifts in demand, coupled with operational and financial constraints, underscore the urgent need for effective strategies to ensure resilience and sustainability. This chapter synthesizes our key findings, explores their broader implications, and offers policy recommendations to strengthen public transportation systems against future crises.

8.1 Summary and implications

The main objective of this research has been to explore the challenges faced by public transportation systems during and after the COVID-19 pandemic, with a focus on understanding the patterns of changes in demand at stations and the factors influencing them, as well as how operators make trade-offs between operational constraints, maintenance of service levels, and long-term passenger flows. Major railway stations in Japan are selected for this research, spanning two years before and after the outbreak. Significant reductions in passenger numbers, financial pressures on public transport operators, and stringent health and safety measures pose significant operational challenges. Due to the unique nature of the outbreak's impact on passengers, we also emphasize the importance of understanding station vitality - a composite measure of ridership and station usage for other purposes - in order to develop countermeasures to mitigate the impact of future crises and improve the resilience of public transport systems.

Chapter 2 provides a comprehensive review of the existing literature on the impacts of the COVID-19 pandemic on public transport, the data sources used to quantify these impacts, and the methodologies used for long-term demand forecasting and frequency planning. Despite the extensive body of work, there are gaps in the current research, particularly in understanding the composite nature of station vitality and the specific factors influencing it, such as passenger flow, commercial activity, and accessibility. Additionally, existing demand forecasting methods often lack the integration of real-time data and dynamic variables, highlighting the need for more robust and adaptive forecasting approaches.

Chapter 3 draws on existing urban resilience theories to propose a comprehensive Governance-Transportation-Mobility-Resilience (GTMR) framework for assessing and improving the resilience of public transportation systems during a pandemic. It provides a summary of commonly adopted transportation-related strategies aimed at controlling the pandemic. The chapter also assesses the effectiveness of transportation-related containment policies during the COVID-19 pandemic and analyzes their impact on system resilience using the GTMR framework. The GTMR framework helps in systematically evaluating the interplay between governance structures, transportation policies, and mobility patterns in enhancing resilience. However, it is not a one-size-fits-all solution and requires adaptation to specific local contexts and conditions to be fully effective.

Chapter 4 focuses on the changes in station dynamics in the short and medium term. Through clustering and regression analysis of data from the regional grids in which the stations are located, it identifies changes in travel behavior in different regions of Japan and explores the reasons behind these changes and their interactions. The research categorizes stations into five distinct groups based on their response to the pandemic. Notably, the analysis highlights that some stations maintained relatively stable demand, while others experienced significant drops that either recovered quickly or remained low in the long term. Specifically, stations functioning as major transportation hubs, accommodating more routes, and with higher absolute passenger volumes like Tokyo, Osaka and Fukuoka were more adversely affected, which may seem intuitive but the nuanced categorization reveals patterns beyond general perceptions. For example, some peripheral stations with mixed land use like Moriya and Meinohama demonstrated greater resilience, providing new insights into the factors that contribute to station vitality during crises: the vitality of the suburban interchange will not be affected much. This can lead to a deeper understanding of the concept of interchange versus hub stations, where hubs usually have a collector function on top of the interchange, i.e. whether the inflow and outflow of vitality is associated with the station.

Chapter 5 uses multiple regression models based on cluster analysis to understand the impact of various factors on station dynamics. For each station, data obtained included land use, point of interest (POI) density, geographic factors, and demographic characteristics. In terms of demographic characteristics, our analyses of population affiliations in station areas indicate that urban stations with dominant local populations are more dynamic and less likely to lose demand during a pandemic. For example, stations such as Akita and Miyazaki have a local population percentage that is above 95% most of the time, and even above 99.5% during a severe pandemic. These stations are often located in remote areas of Japan, suggesting a link between location and travel stickiness and station attractiveness.

Surprisingly, roads and railways were significant negative factors affecting station vitality. This unexpected finding suggests that extensive infrastructure that supports high traffic volumes may limit other land uses that contribute to station vitality, such as commercial and residential areas. The conflict between station accessibility, scale and vitality provides valuable insights for public transport operators to develop targeted interventions. For example, operators can focus on improving business and residential amenities around major transport hubs to balance the negative impacts of large-scale infrastructure, thereby improving the overall vitality and resilience of stations.

In addition to understanding station dynamics, Chapter 6 focuses on predicting station vitality. It evaluates various forecasting techniques, including ARIMAX and LSTM methods, based on their ability to capture complex demand dynamics. The improvements in the ARIMAX model over the ARIMA model suggest that exogenous variables describing policy impacts are crucial. Trends in station activity are better captured based on the percentage of the population affected by the policy rather than the percentage affected by COVID-19. Estimating the affected population involves gathering data on policy measures, such as lockdowns, travel restrictions, and vaccination rates. This data can be sourced from government reports, health department updates, and mobile network data, which provide insights into population movements and behaviors. Combining these data points with demographic information helps to create a comprehensive picture of the affected population.

The LSTM model, while relevant, requires sufficient training data—approximately three waves of data—to achieve accurate predictive power. LSTM can effectively model long-term dependencies and non-linear relationships in time series data, making it suitable for capturing the complex demand dynamics during pandemics. Integrating real-time data into LSTM models can enhance their responsiveness and accuracy. For future pandemics, the ability to estimate the affected population accurately is critical. It implies that real-time data collection and analysis will be vital for developing responsive public transportation strategies. The integration of exogenous variables, such as policy impacts, into forecasting models will enhance predictive accuracy. Public transportation operators should invest in advanced data analytics and establish robust data-sharing agreements with health and government agencies. This proactive approach will enable quicker adaptations to changing conditions, ensuring resilience and sustainability in public transportation systems.

Chapter 7 synthesizes insights from the previous chapters to develop a theoretical model for balancing service quality with operational constraints during a COVID-19 pandemic. This chapter discusses the critical trade-off between maintaining a high level of service, which requires higher operating costs but helps stabilize demand in the long term, and lowering the quality of service to reduce costs, which may lead to a future decline in demand. The analysis emphasizes the need for flexibility in frequency planning to ensure resilience and sustainability. By analyzing different scenarios for low- and high-quality services, the chapter illustrates how operating costs and future demand stability are affected, providing practical insights for public transport operators to make informed decisions that balance cost-effectiveness and demand retention. The government also plays a crucial role in this context. Financial support from governments can ensure service continuity during pandemics through subsidies, grants, or low-interest loans aimed at covering operational costs and maintaining service quality. Establishing policy frameworks to facilitate data sharing between public health authorities and PT operators can enable more accurate demand forecasting and responsive planning. Additionally, government intervention in regulating fare policies and providing guidelines for safe operations can further stabilize the system, ensuring that essential services remain available to the public while safeguarding the long-term sustainability of public transport systems.

Generally, when the revenue-to-expenditure ratio is greater than 30%, there is an option to either maintain the current level of service or reduce it to the expected level after a disaster, but not by more than 20%. If the revenue-to-expenditure ratio is relatively low, then action should be taken promptly to mitigate damage by reducing the level of service. By combining practical insights with policy recommendations, this chapter underscores the importance of a coordinated approach to managing public transportation during crises, ensuring both resilience and sustainability.

8.2 Contribution to existing knowledge

Firstly, we demonstrate the potential of using mobile spatial statistics to study station demand dynamics during events such as the COVID-19 pandemic. Mobile spatial statistics provide a broader source of information for analyzing dynamic demand for various activities, especially during disasters.

We propose the concept of "station vitality" as a comprehensive indicator for measuring and analyzing changes in station dynamics during COVID-19 outbreaks. Unlike previous analyses using other datasets (e.g., smart card data), "station vitality" encompasses a wide range of factors such as passenger flow, commercial activity, accessibility, and overall functionality. This new metric helps provide a more complete picture of station usage and its fluctuations during a crisis, offering a valuable tool for future transportation research and planning.

Secondly, recognizing the far-reaching and potentially long-lasting impacts of pandemics, we address the lack of a framework for assessing the effectiveness of transportation policies in increasing urban resilience during pandemics. To fill this gap, we conducted a comprehensive literature review and developed the Governance-Transportation-Mobility-Resilience (GTMR) framework. This framework offers a structured methodology for assessing and enhancing the resilience of PT systems, guiding policymakers and operators in developing effective strategies to withstand and recover from future crises. By providing a systematic approach to evaluating policy impacts, the GTMR framework can help in making informed decisions that improve both immediate responses and long-term resilience.

Thirdly, we apply methods including clustering algorithms, multiple regression analysis, and deep learning models (e.g., LSTM) to study the impact of COVID-19 on public transportation. By utilizing these methods, this research provides nuanced insights into short-, medium-, and long-term changes in public transportation demand, enriching the existing literature with reliable data-driven findings. We categorize Japan's major train stations into five different clusters based on the proportion of vitality lost during the COVID-19 pandemic, identifying key factors that influence the classification of stations into different clusters. Trade-offs between station positioning and function can affect their resilience during a disaster: stations with high traffic volumes require more road and rail space, which can compress other types of land use in the station area, reducing station vitality significantly once trips are canceled. Conversely, stations with lower overall traffic volumes tend to have more residential and commercial land uses, factors that increase station robustness. This categorization provides valuable insights into the variability of station responses and helps tailor specific interventions to different station types. Although infrastructure changes cannot be made quickly, the study highlights that diverse land-use around stations appears to increase resilience, emphasizing the importance of strategic urban planning.

Fourthly, we provide empirical evidence on the trade-offs between service quality and operational constraints in the context of the COVID-19 pandemic. We highlight the delicate balance that public transport operators must maintain between reducing operating costs and ensuring service quality to maintain passenger demand. By synthesizing findings from various analytical approaches, we offer practical insights and recommendations for public transport operators and policymakers. These insights are essential for shaping future public transportation policies, ensuring resilience, and maintaining the sustainability of public transportation systems in the face of ongoing and future disruptions. The evidence presented underscores the importance of strategic flexibility and the need for robust planning to navigate the uncertainties of future crises.

8.3 Future research directions

While this dissertation comprehensively analyzes the impact of the COVID-19 pandemic on the public transportation system, there are still several areas for further research. Future studies can expand in the following directions to deepen our understanding of public transportation and improve its resilience:

1) Strengthening the concept of station vitality and expanding the scope of the research with data

In this research, the vitality data we applied contain both demographic and origin information. However, these vitality data also include socio-demographic information, such as age and gender, which were not fully utilized. This can be used for profiling to reflect the characteristics of station users. Combining vitality data with survey data from operators, stores, and other businesses, as well as economic loss reports (since these are also based on station vitality), allows us to make a more detailed distinction between travelers and general station vitality. This helps us explore the impact of the COVID-19 pandemic on the station's own businesses, such as restaurants and shopping.

At the micro level, our current data collection uses a 500 x 500 meter grid to ensure uniformity of scale. If data is available for smaller grid areas, it would help to better capture the actual presence at the station. We also regret that the data usually don't have the same scope; for example, population and residence data are collected by ward, while vitality is collected by grid and cannot be smaller due to data collection limitations. Comparing the vitality of stations in different cities from other countries can provide a more complete picture of the resilience and adaptability of public transportation systems.

2) Optimizing data analysis methods

As we learn from Chapter 6, predicting station vitality resilience at an early stage shows ARIMAX to be preferable despite its limitations. An LSTM with a shorter learning period is more suitable for stations in Clusters 4 and 5, which have repetitive patterns during loss and recovery periods. Combining traditional statistical models with machine learning methods, such as the LSTM-X method that integrates exogenous variables with the LSTM model, could improve the accuracy and robustness of demand forecasts. Additionally, more factors that vary over time and are highly correlated with the epidemic need to be collected.

3) Wider application of the resilience framework

The application of the resilience framework presented in Chapter 3 is critical to deepening our understanding of urban resilience in the context of pandemics. This framework provides a global perspective that guides the work of this dissertation in terms of data analysis, forecasting, and operational strategies.

Using the scenario of major railway stations in Japan during the COVID-19 pandemic as an example, the research highlights the importance of both policy-level interventions and operational responses. Short-term policies such as border closures, remote work, and school closures are effective in cutting off virus transmission. However, the sensitivity and responsiveness of public transportation operations need to be improved, rather than passively waiting for negative feedback from mobility (M) data. Strengthening the synergy between governance (G) and operational (T) layers is crucial, as these directly impact resilience (R) in the transportation sector. Reactive approaches, as noted in the case studies in Chapter 7, are less efficient compared to proactive adjustments.

The framework can be adapted and tested in other transportation contexts, such as bus networks, ferry services, and air travel. Each mode of transportation has unique characteristics and operational challenges, and applying the resilience framework across these contexts will provide valuable guidance in enhancing their robustness against future disruptions. Developing disaster-specific resilience key performance indicators (KPIs) and using the framework for scenario planning will help public transportation operators and decision-makers prepare for a range of possible future disruptions.

By pursuing these research directions, future studies can build on this dissertation and contribute to the development of more resilient, efficient, and sustainable public transportation systems worldwide.

Reference

Alessandretti, L. (2022). What human mobility data tell us about COVID-19 spread. *Nature Reviews Physics*, 4(1), 12-13.

Almlöf, E., Rubensson, I., Cebecauer, M., & Jenelius, E. (2021). Who continued travelling by public transport during COVID-19? Socioeconomic factors explaining travel behaviour in Stockholm 2020 based on smart card data. *European Transport Research Review*, 13, 1-13.

Aloi, A., Alonso, B., Benavente, J., Cordera, R., Echániz, E., González, F., ... & Sañudo, R. (2020). Effects of the COVID-19 lockdown on urban mobility: Empirical evidence from the city of Santander (Spain). *Sustainability*, 12(9), 3870.

Arimura, M., Ha, T. V., Okumura, K., & Asada, T. (2020). Changes in urban mobility in Sapporo city, Japan due to the Covid-19 emergency declarations. *Transportation research interdisciplinary perspectives*, 7, 100212.

Armstrong, D. A., Lebo, M. J., & Lucas, J. (2020). Do covid-19 policies affect mobility behaviour? Evidence from 75 Canadian and American cities. *Canadian Public Policy*, 46(S2), S127-S144.

Atabay, F. V., Pagkalinawan, R. M., Pajarillo, S. D., Villanueva, A. R., & Taylar, J. V. (2022, December). Multivariate Time Series Forecasting using ARIMAX, SARIMAX, and RNN-based Deep Learning Models on Electricity Consumption. In 2022 3rd International Informatics and Software Engineering Conference (IISEC) (pp. 1-6). IEEE.

Bao, D., Yin, L., Tian, S., Lv, J., Wang, Y., Wang, J., & Liao, C. (2022). Impact of different transportation modes on the transmission of covid-19: correlation and strategies from a case study in Wuhan, China. *International Journal of Environmental Research and Public Health*, 19(23), 15705.

Bauch, C. T., & Anand, M. (2020). COVID-19: When should quarantine be enforced? *The Lancet Infectious Diseases*, 20(9), 994–995.

Belhadi, A., Kamble, S., Jabbour, C. J. C., Gunasekaran, A., Ndubisi, N. O., & Venkatesh, M. (2021). Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. *Technological Forecasting and Social Change*, 163, 120447.

Bian, Z., Zuo, F., Gao, J., Chen, Y., Venkata, S. S. C. P., Bernardes, S. D., Ozbay, K., Ban, X. J., & Wang, J. (2021). Time lag effects of COVID-19 policies on transportation systems: A comparative study of New York City and Seattle. *Transportation Research Part A: Policy and Practice*, 145, 269–283.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & Von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19(4), 733–752.

Bui, P. L., Chen, T.-L. (Charline), & Wickens, E. (2021). Tourism industry resilience issues in urban areas during COVID-19. *International Journal of Tourism Cities*, 7(3), 861–879.

Cao, Z., Asakura, Y., & Tan, Z. (2020). Balancing node and place value for ridership coordination in transit-oriented development: A case study of Tokyo. *Transportation Research Part D*, 87, 102518.

Carr, A. (2020). COVID-19, indigenous peoples and tourism: A view from New Zealand. *Tourism Geographies*, 22(3), 491–502.

Chang, H. H., Lee, B., Yang, F. A., & Liou, Y. Y. (2021). Does COVID-19 affect metro use in Taipei?. *Journal of transport geography*, 91, 102954.

Chen, A. H., Liang, Y. C., Chang, W. J., Siauw, H. Y., & Minanda, V. (2022). RFM model and K-means clustering analysis of transit traveller profiles: a case study. *Journal of Advanced Transportation*, 2022.

Chen, J., Guo, X., Pan, H., & Zhong, S. (2021). What determines city's resilience against epidemic outbreak: Evidence from China's COVID-19 experience. *Sustainable Cities and Society*, 70, 102892.

Chen, K. L., Brozen, M., Rollman, J. E., Ward, T., Norris, K. C., Gregory, K. D., & Zimmerman, F. J. (2021). How is the COVID-19 pandemic shaping transportation access to health care? *Transportation Research Interdisciplinary Perspectives*, 10, 100338.

Chen, Y., & Zhang, D. (2020). Evaluation of city sustainability using multi-criteria decision-making considering interaction among criteria in Liaoning province China. *Sustainable Cities and Society*, 59, 102211.

Chien, G. C. L., & Law, R. (2003). The impact of the severe acute respiratory syndrome on hotels: A case study of Hong Kong. *International Journal of Hospitality Management*, 22(3), 327–332.

Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., Pastore y Piontti, A., Mu, K., Rossi, L., & Sun, K. (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science*, 368(6489), 395–400.

Choi, T.-M. (2021). Risk analysis in logistics systems: A research agenda during and after the COVID-19 pandemic. *In Transportation Research Part E: Logistics and Transportation Review* (Vol. 145). Pergamon.

Chowdhury, A. Z. (2022). Exploring the Impact of COVID-19 on Taxi Demand in New York City Using Machine Learning (*Doctoral dissertation*, Southern Illinois University at Edwardsville).

Chuwang, D. D., & Chen, W. (2022). Forecasting daily and weekly passenger demand for urban rail transit stations based on a time series model approach. *Forecasting*, 4(4), 904-924.

Cochran, A. L. (2020). Impacts of COVID-19 on access to transportation for people with disabilities. *Transportation Research Interdisciplinary Perspectives*, 8, 100263.

Dai, J., Schmöcker, J.-D., & Sun, W. (2024). Analyzing demand reduction and recovery of major rail stations in Japan during COVID-19 using mobile spatial statistics. *Asian Transport Studies*, 10, 100120.

Dantsuji, T., Sugishita, K., & Fukuda, D. (2023). Understanding changes in travel patterns during the COVID-19 outbreak in the three major metropolitan areas of Japan. *Transportation research part A: policy and practice*, 175, 103762.

Darsena, D., Gelli, G., Iudice, I., & Verde, F. (2020). Safe and reliable public transportation systems (SALUTARY) in the COVID-19 pandemic.

Datola, G. (2023). Implementing urban resilience in urban planning: A comprehensive framework for urban resilience evaluation. *Sustainable Cities and Society*, 98, 104821.

Dingil, A. E., & Esztergár-Kiss, D. (2021). The Influence of the Covid-19 Pandemic on Mobility Patterns: The First Wave's Results. *Transportation Letters*, 13(5–6), 434–446.

Egidi, G., Salvati, L., & Vinci, S. (2020). The long way to tipperary: City size and worldwide urban population trends, 1950–2030. *Sustainable Cities and Society*, 60, 102148.

Faturechi, R., & Miller-Hooks, E. (2015). Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review. Journal of Infrastructure Systems, 21(1), 4014025.

Feng, X., Xiu, C., Bai, L., Zhong, Y., & Wei, Y. (2020). Comprehensive evaluation of urban resilience based on the perspective of landscape pattern: A case study of Shenyang city. *Cities*, 104, 102722.

Fisher, M., & LaMondia, J. J. (2023). Understanding the Temporal, Regional, Demographic, and Policy Factors Influencing Counties' Daily Traffic Volume Reductions in Response to COVID-19. *Transportation research record*, 2677(4), 129-141.

Ganguly, S., Gupta, A., Arora, S., & Arora, N. (2020). Impact of Pandemics. In Indian Institute of Technology & National Institute of Disaster Management (Eds.), Integrated Risk of Pandemic: Covid-19 Impacts, *Resilience and Recommendations* (pp. 107–132). Springer Singapore.

Gaskin, D. J., Zare, H., & Delarmente, B. A. (2021). Geographic disparities in COVID-19 infections and deaths: The role of transportation. *Transport policy*, 102, 35-46.

Ghalehkhondabi, I., Ardjmand, E., Young, W.A. and Weckman, G.R. (2019), "A review of demand forecasting models and methodological developments within tourism and passenger transportation industry", *Journal of Tourism Futures*, Vol. 5 No. 1, pp. 75-93.

Gong, H., Hassink, R., Tan, J., & Huang, D. (2020). Regional resilience in times of a pandemic crisis: The case of COVID-19 in China. *Tijdschrift Voor Economische En Sociale Geografie*, 111(3), 497–512.

Gretzel, U., Fuchs, M., Baggio, R., Hoepken, W., Law, R., Neidhardt, J., Pesonen, J., Zanker, M., & Xiang, Z. (2020). e-Tourism beyond COVID-19: A call for transformative research. *Information Technology & Tourism*, 22(2), 187–203.

Gudmundsson, S. V., Cattaneo, M., & Redondi, R. (2021). Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19. *Journal of Air Transport Management*, 91, 102007.

Gupta, M., Pawar, N. M., & Velaga, N. R. (2021). Impact of lockdown and change in mobility patterns on road fatalities during COVID-19 pandemic. *Transportation letters*, 13(5-6), 447-460.

Gupta, V., & Sahu, G. (2021). Virus Outbreaks and Tourism Resilience Strategies: A Perspective of Asian Countries. In S. Kumar Kulshreshtha (Ed.), Virus Outbreaks and Tourism Mobility (pp. 59–74). Emerald Publishing Limited.

Gössling, S., Scott, D., & Hall, C. M. (2020). Pandemics, tourism and global change: A rapid assessment of COVID-19. *Journal of Sustainable Tourism*, 29(1), 1–20.

Ha, T. V., Asada, T., & Arimura, M. (2023). Changes in mobility amid the COVID-19 pandemic in Sapporo City, Japan: An investigation through the relationship between spatiotemporal population density and urban facilities. *Transportation research interdisciplinary perspectives*, 17, 100744.

Habib, Y., Xia, E., Hashmi, S. H., & Fareed, Z. (2021). Non-linear spatial linkage between COVID-19 pandemic and mobility in ten countries: A lesson for future wave. *Journal of infection and public health*, 14(10), 1411-1426.

Hall, C. M., Prayag, G., & Amore, A. (2017). Tourism and resilience: Individual, organisational and destination perspectives. Channel View Publications.

Hall, C. M., Scott, D., & Gössling, S. (2020). Pandemics, transformations and tourism: Be careful what you wish for. *Tourism Geographies*, 22(3), 577–598.

Halvorsen, A., Wood, D., Jefferson, D., Stasko, T., Hui, J., & Reddy, A. (2023). Examination of New York City Transit's bus and subway ridership trends during the COVID-19 pandemic. *Transportation Research Record*, 2677(4), 51-64.

Halyal, S., Mulangi, R. H., & Harsha, M. M. (2022). Forecasting public transit passenger demand: With neural networks using APC data. *Case Studies on Transport Policy*, 10(2), 965-975.

Hamid, H. A., Hassan, A., Wah, Y. B., & Amin, N. A. M. (2018, October). Investigating the power of goodness-of-fit test for multinomial logistic regression using K-Means clustering technique. In AIP Conference Proceedings (Vol. 2013, No. 1). AIP Publishing.

Hara, Y., & Yamaguchi, H. (2021). Japanese travel behavior trends and change under COVID-19 state-of-emergency declaration: Nationwide observation by mobile phone location data. *Transportation Research Interdisciplinary Perspectives*, 9, 100288.

Haraguchi, M., Nishino, A., Kodaka, A., Allaire, M., Lall, U., Kuei-Hsien, L., Onda, K., Tsubouchi, K., & Kohtake, N. (2022). Human mobility data and analysis for urban resilience: A systematic review. *Environment and Planning B: Urban Analytics and City Science*, 49(5), 1507–1535.

Harantová, V., Mazanec, J., Štefancová, V., Mašek, J., & Foltýnová, H. B. (2023). Two-step cluster analysis of passenger mobility segmentation during the COVID-19 pandemic. *Mathematics*, 11(3), 583.

Hashimoto, M., Mas, E., Egawa, S., Sano, D., & Koshimura, S. (2022). Flood Hazard-Based Evacuation Curve Using Mobile Spatial Statistics. Available at SSRN 4271169.

Hasselwander, M., Tamagusko, T., Bigotte, J. F., Ferreira, A., Mejia, A., & Ferranti, E. J. (2021). Building back better: The COVID-19 pandemic and transport policy implications for a developing megacity. *Sustainable Cities and Society*, 69, 102864.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9(8), 1735-1780.

Hyland, M., Hong, Z., de Farias Pinto, H. K. R., & Chen, Y. (2018). Hybrid cluster-regression approach to model bikeshare station usage. *Transportation Research Part A: Policy and Practice*, 115, 71-89.

Hynes, W., Trump, B., Love, P., & Linkov, I. (2020). Bouncing forward: A resilience approach to dealing with COVID-19 and future systemic shocks. *Environment Systems and Decisions*, 40(2), 174–184.

Ichiro O., Satoshi T., Masayuki T., Daizo I., Tomohiro N. (2013). "Supporting grown in society and industry using statistical data from mobile terminal networks–overview of mobile spatial statistics." *NTT DOCOMO Technical Journal*, 14(3), 4-9.

Jaccard, I. (2022). The Trade-Off between Public Health and the Economy in the Early Stage of the COVID-19 Pandemic. *SSRN Electronic Journal*.

Jamal, T., & Budke, C. (2020). Tourism in a world with pandemics: Local-global responsibility and action. *Journal of Tourism Futures*.

Jenelius, E. (2022). Rail transport resilience to demand shocks and COVID-19. In Rail Infrastructure Resilience (pp. 65-79). Woodhead Publishing.

Jenelius, E., & Cebecauer, M. (2020). Impacts of COVID-19 on public transport ridership in Sweden: Analysis of ticket validations, sales and passenger counts. *Transportation Research Interdisciplinary Perspectives*, 8, 100242.

Jiao, E. X., & Chen, J. L. (2019). Tourism forecasting: A review of methodological developments over the last decade. *Tourism Economics*, 25(3), 469-492.

Jiao, F., Huang, L., Song, R., & Huang, H. (2021). An improved STL-LSTM model for daily bus passenger flow prediction during the COVID-19 pandemic. *Sensors*, 21(17), 5950.

Kim, J., & Kwan, M. P. (2021). The impact of the COVID-19 pandemic on people's mobility: A longitudinal study of the US from March to September of 2020. *Journal of Transport Geography*, 93, 103039.

Kolozsvári, L. R., Bérczes, T., Hajdu, A., Gesztelyi, R., Tiba, A., Varga, I., ... & Zsuga, J. (2021). Predicting the epidemic curve of the coronavirus (SARS-CoV-2) disease (COVID-19) using artificial intelligence: An application on the first and second waves. *Informatics in Medicine Unlocked*, 25, 100691.

Ku, D. G., Um, J. S., Byon, Y. J., Kim, J. Y., & Lee, S. J. (2021). Changes in passengers' travel behavior due to COVID-19. *Sustainability*, 13(14), 7974.

Lam, C., Waldhorn, R., Toner, E., Inglesby, T. V., & O'Toole, T. (2006). The prospect of using alternative medical care facilities in an influenza pandemic. *Biosecurity and Bioterrorism: Biodefense Strategy, Practice, and Science*, 4(4), 384–390.

Lancet, T. (2020a). COVID-19: Fighting panic with information. *Lancet (London, England)*, 395(10224), 537.

Lancet, T. (2020b). COVID-19: Learning from experience. *Lancet (London, England)*, 395(10229), 1011.

Lew, A. A. (2014). Scale, change and resilience in community tourism planning. *Tourism Geographies*, 16(1), 14–22.

Liu, S., & Yamamoto, T. (2022). Role of stay-at-home requests and travel restrictions in preventing the spread of COVID-19 in Japan. *Transportation Research Part A: Policy and Practice*, 159, 1-16.

Liu, X., Li, S., Xu, X., & Luo, J. (2021). Integrated natural disasters urban resilience evaluation: The case of China. *Natural Hazards*, 107(3), 2105–2122.

Lu, Q. L., Mahajan, V., Lyu, C., & Antoniou, C. (2024). Analyzing the impact of fare-free public transport policies on crowding patterns at stations using crowdsensing data. *Transportation Research Part A: Policy and Practice*, 179, 103944.

Ma, S., Li, S., & Zhang, J. (2023). Spatial and deep learning analyses of urban recovery from the impacts of COVID-19. *Scientific Reports*, 13, 2447.

Mahajan, V., Cantelmo, G., & Antoniou, C. (2021). Explaining demand patterns during COVID-19 using opportunistic data: A case study of the city of Munich. *European Transport Research Review*, 13(1), 26.

Malhotra, R., & Venkatesh, U. (2009). Pre-crisis period planning: Lessons for hospitality and tourism. Worldwide Hospitality and Tourism Themes.

Masayuki T., Tomohiro N., Motonari K. (2013). "Population estimation technology for mobile spatial statistics." *NTT DOCOMO Technical Journal*, 14(3), 10-15.

Matei, D., Chiriță, V., Ștefan cel Mare University, History and Geography Faculty, Department of Geography, Suceava, România, Lupchian, M. M., & Ștefan cel Mare University, History and Geography Faculty, Department of Geography, Suceava, România. (2021). GOVERNANCE AND TOURISM RESILIENCE DURING THE COVID19 CRISIS. CASE STUDY BUKOVINA, ROMANIA. *GeoJournal of Tourism and Geosites*, 34(1), 256–262.

McCartney, G. (2021). The impact of the coronavirus outbreak on Macao. From tourism lockdown to tourism recovery. *Current Issues in Tourism*, 24(19), 2683–2692.

McCartney, G., Pinto, J., & Liu, M. (2021). City resilience and recovery from COVID-19: The case of Macao. *Cities*, 112, 103130.

Meerow, S., Newell, J. P., & Stults, M. (2016). Defining urban resilience: A review. *Landscape and Urban Planning*, 147, 38–49.

Milenković, M., Švadlenka, L., Melichar, V., Bojović, N., & Avramović, Z. (2018). SARIMA modelling approach for railway passenger flow forecasting. *Transport*, 33(5), 1113-1120.

Mo, B., Koutsopoulos, H., & Zhao J. (2022). Inferring passenger responses to urban rail disruptions using smart card data: A probabilistic framework. *Transportation Research Part E: Logistics and Transportation Review*, 159, 102628.

Niewiadomski, P. (2020). COVID-19: From temporary de-globalisation to a re-discovery of tourism? *Tourism Geographies*, 22(3), 651–656.

Niu, Q., Wang, G., Liu, B., Zhang, R., Lei, J., Wang, H., & Liu, M. (2023). Selection and prediction of metro station sites based on spatial data and random forest: a study of Lanzhou, China. *Scientific Reports*, 13(1), 22542.

Östh, J., Toger, M., Türk, U., Kourtit, K., & Nijkamp, P. (2023). Leisure mobility changes during the COVID-19 pandemic–An analysis of survey and mobile phone data in Sweden. *Research in Transportation Business & Management*, 100952.

de Paiva, I. V. L., de Assunção, M. V. D., Medeiros, M., de Souza Paes, D. C. A., & Moreira, L. N. R. (2021). The influence of passenger traffic in brazilian airports on increased cases of covid-19. *Holos*, 4, 1-23.

Peak, C. M., Kahn, R., Grad, Y. H., Childs, L. M., Li, R., Lipsitch, M., & Buckee, C. O. (2020). Individual quarantine versus active monitoring of contacts for the mitigation of COVID-19: A modelling study. *The Lancet Infectious Diseases*, 20(9), 1025–1033.

Prayag, G. (2020). Time for reset? COVID-19 and tourism resilience. *Tourism Review International*, 24(2–3), 179–184.

Rasca, S., Markvica, K., & Ivanschitz, B. P. (2021). Impacts of COVID-19 and pandemic control measures on public transport ridership in European urban areas–The cases of Vienna, Innsbruck, Oslo, and Agder. *Transportation Research Interdisciplinary Perspectives*, 10, 100376.

Rathnayake, D., Clarke, M., & Jayasinghe, V. I. (2021). Health system performance and health system preparedness for the post-pandemic impact of COVID-19: A review. *International Journal of Healthcare Management*, 14(1), 250–254.

Rezvani, S. M., De Almeida, N. M., Falcão, M. J., & Duarte, M. (2022). Enhancing urban resilience evaluation systems through automated rational and consistent decision-making simulations. *Sustainable Cities and Society*, 78, 103612.

Ribeiro, H. V., Sunahara, A. S., Sutton, J., Perc, M., & Hanley, Q. S. (2020). City size and the spreading of COVID-19 in Brazil. *PloS one*, 15(9), e0239699.

Ribeiro, P. J. G., & Pena Jardim Gonçalves, L. A. (2019). Urban resilience: A conceptual framework. *Sustainable Cities and Society*, 50, 101625.

Ritchie, B. W., & Jiang, Y. (2019). A review of research on tourism risk, crisis and disaster management: Launching the annals of tourism research curated collection on tourism risk, crisis and disaster management. *Annals of Tourism Research*, 79, 102812.

Roman, M., Roman, M., Grzegorzewska, E., Pietrzak, P., & Roman, K. (2022). Influence of the COVID-19 Pandemic on Tourism in European Countries: Cluster Analysis Findings. *Sustainability*, 14(3), 1602.

Roosa, K., Lee, Y., Luo, R., Kirpich, A., Rothenberg, R., Hyman, J. M., Yan, P., & Chowell, G. (2020). Real-time forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020. *Infectious Disease Modelling*, 5, 256–263.

Ruan, J., Chen, Y., & Yang, Z. (2021). Assessment of temporal and spatial progress of urban resilience in Guangzhou under rainstorm scenarios. *International Journal of Disaster Risk Reduction*, 66, 102578.

Safitri, N. D., & Chikaraishi, M. (2022). Impact of transport network disruption on travel demand: A case study of the July 2018 heavy rain disaster in Japan. *Asian Transport Studies*, 8, 100057.

Santiago-Iglesias, E., Schmöcker, J. D., Carpio-Pinedo, J., García-Palomares, J.C. and Sun, W.Z. (2023). Activity Reduction as Resilience Indicator: Evidence with Filomena Data. *Findings. Section: Resilience Findings*, https://doi.org/10.32866/001c.88980.

Schmöcker, J.-D. (2021). Estimation of city tourism flows: Challenges, new data and COVID. *Transport Reviews*, 41(2), 137–140.

Shimamoto, H., & Kusubaru, R. (2023). Evaluation of the short-and long-term impacts of the COVID-19 pandemic on bus ridership in Miyazaki City, Japan. *Asian Transport Studies*, 9, 100098.

Siewwuttanagul, S., & Jittrapirom, P. (2023). The impact of COVID-19 and related containment measures on Bangkok's public transport ridership. *Transportation Research Interdisciplinary Perspectives*, 17, 100737.

Sigala, M. (2020). Tourism and COVID-19: Impacts and implications for advancing and resetting industry and research. *Journal of Business Research*, 117, 312–321.

Smart Cities Dive. (2024, June 17). Public transit in the post-pandemic world: Views diverge at congressional hearing. Smart Cities Dive. https://www.smartcitiesdive.com/news/public-transit-post-pandemic-congress/719068/

Song, A., Lee, S., Wong, S., Sydney Greater, & Seoul. (2023). A machine learning approach to analyzing spatiotemporal impacts of mobility restriction policies on infection rates. *Transportation Research Part A*, 176, 103795.

Su, Y., & Ye, Y. (2020, October). Daily Passenger Volume Prediction in the Bus Transportation System using ARIMAX Model with Big Data. In 2020 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC) (pp. 291-300). IEEE.

Sun, W., Kobayashi, H., Nakao, S., & Schmöcker, J. D. (2023). On the Relationship Between Crowdsourced Sentiments and Mobility Trends During COVID-19: A Case Study of Kyoto. *Data Science for Transportation*, 5(3), 17.

Sun, W., Schmöcker, J.-D., & Nakao, S. (2022). Restrictive and stimulative impacts of COVID-19 policies on activity trends: A case study of Kyoto. *Transportation Research Interdisciplinary Perspectives*, 13, 100551.

Sydnor-Bousso, S., Stafford, K., Tews, M., & Adler, H. (2011). Toward a resilience model for the hospitality & tourism industry. *Journal of Human Resources in Hospitality & Tourism*, 10(2), 195–217.

Tan, L., & Ma, C. (2021). Choice behavior of commuters' rail transit mode during the COVID-19 pandemic based on logistic model. *Journal of Traffic and Transportation Engineering (English Edition)*, 8(2), 186-195.

Tashiro, A., & Shaw, R. (2020). COVID-19 pandemic response in Japan: What is behind the initial flattening of the curve?. *Sustainability*, 12(13), 5250.

Tatsu H., Yuki H., Atsushi S. (2017), Analysis on change of visitors before and after the open of high speed rail using mobile spatial statistics. *Journal of the Eastern Asia Society for Transportation Studies*, 12, 959-974.

Taylor, B. D., & Fink, C. N. (2003). The factors influencing transit ridership: A review and analysis of the ridership literature.

Teixeira, J. F., & Lopes, M. (2020). The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York's Citi Bike. *Transportation Research Interdisciplinary Perspectives*, 6, 100166.

Vickerman, R. (2021). Will Covid-19 put the public back in public transport? A UK perspective. *Transport Policy*, 103, 95-102.

Vongvanich, T., Sun, W., & Schmöcker, J.-D. (2023). Explaining and Predicting Station Demand Patterns Using Google Popular Times Data. Data *Science for Transportation*, 5(10).

Wang, B., Han, S., Ao, Y., & Liao, F. (2022). Evaluation and Factor Analysis for Urban Resilience: A Case Study of Chengdu–Chongqing Urban Agglomeration. *Buildings*, 12(7), 962.

Wang, H., & Noland, R. B. (2021). Bikeshare and subway ridership changes during the COVID-19 pandemic in New York City. *Transport Policy*, 106, 262–270.

Wang, J., Huang, J., Yang, H., & Levinson, D. (2022). Resilience and recovery of public transport use during COVID-19. npj *Urban Sustainability*, 2(1), 18.

Wang, Y., Liu, Y., Struthers, J., & Lian, M. (2021). Spatiotemporal characteristics of the COVID-19 epidemic in the United States. *Clinical infectious diseases*, 72(4), 643-651.

Wielechowski, M., Czech, K., & Grzęda, Ł. (2020). Decline in Mobility: Public Transport in Poland in the time of the COVID-19 Pandemic. *Economies*, 8(4), 78.

Wilder-Smith, A., & Freedman, D. O. (2020). Isolation, quarantine, social distancing and community containment: Pivotal role for old-style public health measures in the novel coronavirus (2019-nCoV) outbreak. *Journal of Travel Medicine*.

Wilder-Smith, A., & Osman, S. (2020). Public health emergencies of international concern: A historic overview. *Journal of Travel Medicine*, 27(8), taaa227.

Wu, J., Deng, Y., & Chen, C. (2023). Matching Degree Between Ridership and Vitality of Shanghai Suburban Rail Sites. *Journal of Tongji University (Natural Science)*, 51(7):1105~1113.

Wu, L., Chikaraishi, M., Nguyen, H. T., & Fujiwara, A. (2021). Analysis of post-disaster population movement by using mobile spatial statistics. *International Journal of Disaster Risk Reduction*, 54, 102047.

Xu, W., Cong, J., Proverbs, D., & Zhang, L. (2021). An Evaluation of Urban Resilience to Flooding. *Water*, 13(15), 2022.

Xun, X., & Yuan, Y. (2020). Research on the urban resilience evaluation with hybrid multiple attribute TOPSIS method: An example in China. *Natural Hazards*, 103(1), 557–577.

Yamaguchi, H., Nakayama, S. (2023). Pattern analysis of Japanese long-distance travel change under the COVID-19 pandemic. *Transportation Research Part A*, 176, 103805.

Yan, X., & Zhu, Z. (2021). Quantifying the impact of COVID-19 on e-bike safety in China via multi-output and clustering-based regression models. *PLoS one*, 16(8), e0256610.

Yang, H., Dijst, M., Witte, P., Van Ginkel, H., & Yang, W. (2018). The spatial structure of high speed railways and urban networks in China: A flow approach. *Tijdschrift voor economische en sociale geografie*, 109(1), 109-128.

Yang, J., Cao, J., & Zhou, Y. (2021). Elaborating non-linear associations and synergies of subway access and land uses with urban vitality in Shenzhen. *Transportation Research Part A: Policy and Practice*, 144, 74-88.

Yang, Y., Altschuler, B., Liang, Z., & Li, X. R. (2021). Monitoring the global COVID-19 impact on tourism: The COVID19tourism index. *Annals of Tourism Research*, 90, 103120.

Zhang, N., Jia, W., Wang, P., Dung, C. H., Zhao, P., Leung, K., ... & Li, Y. (2021). Changes in local travel behaviour before and during the COVID-19 pandemic in Hong Kong. *Cities*, 112, 103139.

Zhang, X., Miller-Hooks, E., & Denny, K. (2015). Assessing the role of network topology in transportation network resilience. *Journal of Transport Geography*, 46, 35–45.

Zhao, R., Fang, C., Liu, J., & Zhang, L. (2022). The evaluation and obstacle analysis of urban resilience from the multidimensional perspective in Chinese cities. *Sustainable Cities and Society*, 86, 104160. https://doi.org/10.1016/j.scs.2022.104160

Zhao, X., Wu, Y. P., Ren, G., Ji, K., & Qian, W. W. (2019). Clustering analysis of ridership patterns at subway stations: A case in Nanjing, China. *Journal of Urban Planning and Development*, 145(2), 04019005.

Zhou, H., Wang, Y., Huscroft, J. R., & Bai, K. (2021). Impacts of COVID-19 and anti-pandemic policies on urban transport—an empirical study in China. *Transport policy*, 110, 135-149.

Zhou, Y., Wang, J., & Yang, H. (2019). Resilience of transportation systems: Concepts and comprehensive review. *IEEE Transactions on Intelligent Transportation Systems*, 20(12), 4262–4276.

Zhu, Z., Zhang, Y., Qiu, S., Zhao, Y., Ma, J., & He, Z. (2023). Ridership Prediction of Urban Rail Transit Stations Based on AFC and POI Data. *Journal of Transportation Engineering*, Part A: Systems, 149(9), 04023077.

Zuniga-Teran, A. A., Gerlak, A. K., Mayer, B., Evans, T. P., & Lansey, K. E. (2020). Urban resilience and green infrastructure systems: Towards a multidimensional evaluation. *Current Opinion in Environmental Sustainability*, 44, 42–47.