Delft University of Technology
Faculty of Civil Engineering and Geosciences,
Technology, Policy and Management,
and Mechanical Engineering

The Interplay of Crowding, Headway, and Route Overlapping: Implications for Public Transport System Design and Operations

by

Allan David Guzmán Fallas

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Thesis committee:

Chair:	**Prof. Dr. Oded Cats**	TU Delft
Supervisor:	**Dr. Ir. Maarten Kroesen**	TU Delft
Supervisor:	**Dr. Ir. Jaime Soza Parra**	Utrecht University
Supervisor:	**Lucas Spierenburg**	TU Delft
External advisor:	**Dr. Daniel J. Reck**	TPG

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Preface

This project marks and end to my master's studies at TU Delft. I want to express my gratitude to all the people involved in this part of my life; classmates, professors and TU Delft staff as well. It is an honor for me to be a TU Delft alumni. I dreamed about this day for a long time and now I look back and see that is was all I wanted and more.

I want to give special thanks to my committee, starting with Oded Cats, who trusted me with a topic and saw the potential of my research proposal and agreed to be the chair of the committee, to Maarten Kroesen who guided me trough modelling what at first looked dawnting and I ended up enjoying it. And Finally to Jaime Soza Parra, who kept meeting with me every week, guided me, and gave me his advice, and kept believing in the project even when I had my own doubts.

My last words of this preface go to my wife, who is the most amazing human being I have ever met. Thank you for believing in me, for taking the jump into the unkwon with me, moving to a different continent just to help me achieve my dreams. I could not have done it without you.

Enjoy reading :)

Allan Guzmán Fallas Delft, 25-08-2025

Executive summary

Public transport systems are a cornerstone of sustainable urban mobility, offering high-capacity, energy-efficient travel that alleviates congestion and reduces emissions. Yet, the effectiveness of these systems is frequently undermined by operational inefficiencies—most notably, in-vehicle crowding. This thesis investigates the critical interplay between in-vehicle crowding, headway variability, and route overlapping, with a focus on understanding how these factors interact to shape passenger comfort and transit service reliability.

The central question guiding this research is how much of the variability in in-vehicle crowding can be explained by fluctuations in vehicle headways, and to what extent overlapping transit routes exacerbate this relationship. This inquiry is motivated by the observed instability in high-frequency bus and tram corridors, where uneven headways and shared route segments often lead to service bunching, passenger surges, and highly variable load distributions. Despite the wealth of literature describing these phenomena qualitatively, there remains a lack of robust empirical models that quantify their combined effects using operational data.

To address this gap, a data-driven methodology was developed using detailed records from Automatic Vehicle Location (AVL) and Automatic Passenger Count (APC) systems. These datasets were integrated and harmonized with GTFS schedule information to construct a fine-grained panel of vehicle stop events. Each observation in the dataset corresponds to a single vehicle-stop interaction and includes features such as observed headway, boarding and alighting counts, vehicle type, and the degree of route overlapping at that location.

An ordered logistic regression model with random effects was employed to estimate the relationship between these variables and an ordinal measure of passenger comfort, defined on a five-point scale. The model accounts for unobserved heterogeneity at the stop-day-line level and enables consistent inference on the effects of service irregularity and network design on crowding.

The findings reveal that headway variability is a primary driver of in-vehicle crowding. When actual headways deviate significantly from the schedule, vehicles tend to experience uneven passenger loads, with late arrivals absorbing accumulated demand and becoming overcrowded. Line overlapping further compounds this effect by introducing operational interdependencies between routes. Shared corridor segments, while beneficial in increasing perceived frequency, also intensify the risk of bunching and uneven load distribution, especially in the absence of coordinated dispatching.

Additional factors, such as vehicle type and corridor-level service frequency, influence passenger comfort but do not fully offset the negative effects of headway irregularity. Notably, articulated vehicles and high-frequency services offer some mitigation, yet remain vulnerable to demand surges and dwell time extensions when bunching occurs.

This thesis contributes to both academic literature and practical transit planning. Scientifically, it advances empirical modeling of crowding by incorporating both temporal service irregularity and spatial network structure. The proposed framework demonstrates how large-scale operational datasets can be leveraged to inform service planning, reliability analysis, and network design. Societally, the research supports the development of strategies that improve service quality—such as dynamic headway control, coordinated scheduling across overlapping lines, and targeted infrastructure enhancements.

The policy implications are significant. Transit agencies can utilize these insights to implement proactive interventions, such as holding controls, transit signal priority, and real-time passenger information systems. Furthermore, the findings emphasize the importance of designing networks with balanced overlapping and the need for continuous performance monitoring to identify and mitigate emerging crowding issues.

While the model captures key operational dynamics, it does not account for all sources of variability, including weather, special events, or individual travel behavior. Future research could explore the integration of predictive machine learning models, real-time feedback systems, or multimodal interactions to further enhance crowding management.

In conclusion, this thesis underscores the importance of addressing headway variability and line overlapping as interconnected challenges. By quantifying their impacts on in-vehicle crowding, it offers a valuable toolkit for designing more resilient, efficient, and passenger-centered public transport systems.

Contents

Chapter 1

Introduction

Public transportation systems are essential in modern urban environments, playing a pivotal role in reducing traffic congestion, lowering per-capita emissions, and cutting energy consumption by moving large numbers of passengers in single vehicles rather than as individual cars. By maximizing vehicle occupancy and leveraging dedicated rights-of-way or high-occupancy lanes, public transport networks achieve far higher throughput and energy efficiency per passenger-kilometer than private automobiles. Moreover, efficient public transport service supports land-use patterns that favor densification, further reducing urban sprawl and associated infrastructure costs.

However, one of the most persistent challenges in these systems is in-vehicle crowding, which not only undermines passenger comfort and satisfaction but also diminishes operational efficiency. When vehicles exceed their design capacity, boarding and alighting times increase, dwell times become more variable, and the risk of delays propagates through the network. These disruptions force operators to pad schedules, reduce reliability, and allocate additional resources, actions that drive up operating costs and can ultimately discourage ridership.

A central determinant of crowding is headway variability, defined as a statistical metric that computes the deviation between the actual and scheduled time interval for consecutive vehicles. Formally, if two vehicles are planned to depart every five minutes, but one departs after three minutes and the next after seven, the resulting variability creates uneven passenger accumulation at stops: the late vehicle picks up a large backlog of waiting passengers, while the early one may run nearly empty. Over time, these imbalances intensify, leading to cyclic patterns of overcrowding and under-utilization that erode service quality and passenger confidence, also known as vehicle bunching.

This thesis explores the complex relationships among in-vehicle crowding, headway variability, and network design, placing particular emphasis on the role of line overlapping. Line overlapping occurs when two or more public transport routes share a segment of their corridors. While overlapping can enhance actual frequency and offer riders more route options, it also introduces operational inter-dependencies: delays on one route can spill over to the other, exacerbating headway irregularities and triggering bus or tram bunching. In high-frequency systems, these effects combine to generate uneven passenger loads and heightened levels of crowding, creating a feedback loop in which irregular service intervals fuel crowding, and crowding in turn leads to further reliability deterioration.

This chapter introduces the primary issues addressed in this research and outlines the scope, objectives, and contributions of the thesis. Section 1.1 provides a detailed description of the core problem, including the mechanisms linking headway variability and line overlapping to crowding. Section 1.2 outlines the research scope, objectives, and guiding questions. In Section 1.3, the scientific and societal contributions of the research are discussed in depth. Finally, Section 1.4 presents an overview of the thesis structure.

1.1. Problem Description

Public transportation is vital for urban mobility, connecting people to jobs, education, and essential services. However, many cities face challenges in providing efficient, affordable, reliable and passenger comfort. One of the most significant challenges is crowding, which can lead to decreased service quality and user dissatisfaction. This section delves into the factors contributing to crowding, with a particular focus on headway variability and network design, including the phenomenon of line overlapping. These factors exacerbate passenger accumulation at certain points, leading to unpredictable and often unpleasant travel experiences. Addressing these issues requires a multifaceted approach, encompassing optimized scheduling, improved infrastructure, and innovative demand management strategies. Data-driven solutions and real-time monitoring are crucial for proactive adjustments.

1.1.1. Problem Context

Efficient public transport systems are essential for improving urban living conditions by reducing car dependency, traffic congestion, and emissions (Figliozzi et al., 2012). However, systems such as buses, trams, and trolleybuses often suffer from in-vehicle crowding when demand exceeds capacity at specific times or locations. Crowding is not merely an inconvenience; it significantly decreases passenger comfort and satisfaction, thereby potentially reducing ridership.

Crowding levels are influenced by several factors including passenger demand, vehicle capacity, and service frequency. Headway variability, the inconsistency in time intervals between consecutive vehicles, plays a critical role in this dynamic. Unpredictable factors such as traffic conditions, road incidents, or fluctuations in passenger demand contribute to irregular headways. These disruptions cause some vehicles to be overcrowded while others remain underutilized. The challenge is further compounded in systems where overlapping routes are common. When multiple lines share a corridor, the synchronization of headways across different services becomes more complex, often resulting in bus bunching, where vehicles arrive in close succession. Such bunching amplifies the uneven distribution of passengers and prolongs dwell times at stops, thereby intensifying in-vehicle crowding (Drabicki et al., 2023; Godachevich & Tirachini, 2021).

1.1.2. Problem Statement and Knowledge Gaps

Although the qualitative relationship between headway variability and crowding is well-documented, the quantitative aspects of this relationship remain underexplored. Previous studies, such as Chen and Liu (2011), have attempted to assess the impact of headway variability on crowding using limited, manually collected data. However, the use of large-scale datasets, such as Automatic Vehicle Location (AVL) and Automatic Passenger Count (APC) data, has not been fully exploited in this context.

This thesis addresses this knowledge gap by developing a data-driven analytical framework to empirically explore and model the interdependent relationships among crowding, headway variability, and overlapping service configurations in public transport networks. Leveraging AVL and APC data, the study aims to derive measurable indicators that capture the systemic feedback loops and variability patterns across different operational scenarios. The ultimate goal is to provide insights that inform more resilient network design principles and targeted control strategies for improving service reliability and passenger experience in overlapping and high-demand corridors.

1.2. Research Design

1.2.1. Research Scope

This research focuses on bus, tram, and trolleybus systems, as these modes offer greater flexibility for network adjustments (e.g., rerouting, modifying stop locations) compared to more rigid systems like metros. These systems also frequently share road space with other vehicles, introducing unique challenges related to headway variability. The study emphasizes two primary factors: headway variability and network design, with a special focus on corridor effects and line overlapping.

Headway Variability in Overlapping vs. Non-Overlapping Segments

Headway variability is a well-documented driver of uneven passenger loads and crowding (Tirachini et al., 2016; Drabicki et al., 2023). In this research, we quantify headway variability in two complementary ways: the percentage difference between actual and scheduled headway at each stop and the occurrence of successive vehicles arriving within a short threshold, indicating service compression. We compare these metrics across overlapping segments, where two or more lines share the same corridor, and non-overlapping segments to isolate the amplifying effect of network structure on variability and crowding.

Network Structure and Corridor Effects

The geometry of the public transport network, particularly the degree of route overlap on shared arcs, shapes passenger distribution and operational interactions. Overlapping lines can increase effective frequency but also introduce inter-line dependencies that magnify the impact of delays. By focusing on corridor segments with varying levels of line overlap, we assess how the number of overlapping line contribute to crowding levels and the role of aggregate corridor frequency; summing all services on the arc, in mitigating or exacerbating crowding under different headway variability regimes.

1.2.2. *Research Objectives and Research Questions*

The primary objective of this research is to develop a statistical model that estimates how headway variability and line overlapping affect in-vehicle crowding; using a data-driven approach. By analyzing real-world data from public transport systems, this study seeks to quantify the interactions among these factors and provide actionable insights for optimizing service planning and delivery.

The central research question is:

> ***How much of the variability in in-vehicle crowding levels can be explained by headway variability in bus or tram lines, and what is the impact of line overlapping on this relationship?***

To address this overarching question, the following sub-questions will be investigated:

1. **What is the theoretical relationship between in-vehicle crowding, headway variability, and line overlapping in a public transport system?**

   This question aims to establish a conceptual framework by reviewing existing literature and theoretical models. Understanding the theoretical underpinnings will help delineate how each factor influences crowding and provide a basis for subsequent empirical analysis. By clarifying the inter-dependencies among these variables, this research can identify potential mechanisms and pathways that lead to crowding in public transport systems.

2. **How can AVL and APC data be used to accurately measure and analyze in-vehicle crowding and headway variability?**

   The ability to reliably quantify crowding and headway variability is critical for empirical analysis. This question addresses the methodological challenges associated with processing and interpreting large-scale operational datasets. By establishing robust data collection and analysis methods, the research will improve the accuracy of performance assessments in public transportation systems and enable more precise identification of operational issues.

3. **What is the result of incorporating both headway variability and line overlapping to crowding models in public transport?**

   Current models of in-vehicle crowding often overlook the combined effects of headway variability and overlapping routes. Enhancing these models to include the impact of network design factors is essential for capturing the complex dynamics that drive passenger load imbalances. This question seeks to refine and extend empirical models, thereby offering a more comprehensive tool for public transport system evaluation and planning. The improved models could lead to more effective strategies for managing crowding and improving service reliability.

1.3. Scientific and Societal Contributions

This thesis contributes both to academic research and to societal advancements in urban mobility. The outcomes of this study are expected to provide new insights that lead to better management of public transportation systems, enhancing both operational efficiency and the overall passenger experience.

1.3.1. *Scientific Contributions*

This research offers several key scientific contributions:

Data-Driven Modeling:
The primary scientific contribution is the development of a quantitative, data-driven model that integrates headway variability and network design factors, especially line overlapping, to predict in-vehicle crowding. By leveraging large-scale Automatic Passenger Count (APC) and Automatic Vehicle Location (AVL) datasets, the model provides an empirical basis for understanding the dynamics of passenger loads. This approach not only advances current modeling techniques in transportation research but also sets a precedent for using operational data to quantify complex interactions within public transport systems.

Enhanced Theoretical Framework:
By rigorously linking headway variability, line overlapping, and crowding, this research expands the theoretical framework that describes public transport system performance. The study synthesizes insights from multiple strands of literature, providing a clearer conceptual basis for how operational factors interrelate. This enhanced framework can serve as a foundation for future research, guiding subsequent empirical investigations and theoretical advancements in public transportation studies.

Empirical Validation:
Through the application of the developed models to real-world data, this research provides concrete empirical validation of the theoretical predictions. By demonstrating how headway variability and overlapping routes contribute to in-vehicle crowding, the study offers robust evidence that supports and refines existing models. This empirical grounding is essential for ensuring that theoretical insights translate into practical solutions in the field of transportation engineering.

1.3.2. Societal Contributions

Beyond academic contributions, the findings provide practical value for public transport operators and planners. By quantifying how headway variability and route overlap influence in-vehicle crowding, the study offers evidence to support targeted interventions such as holding strategies, better coordination of overlapping lines, or adjustments in schedule design. These measures can help reduce the most disruptive crowding episodes and improve service predictability without necessarily requiring large investments. For passengers, this translates into fewer extreme discomfort situations and more consistent reliability. At the system level, even modest improvements in regularity can make public transport a more dependable alternative to private cars, thereby supporting wider urban mobility and sustainability goals.

1.4. Structure of the thesis

The remainder of this thesis is organized into seven chapters. Chapter 2 presents a comprehensive literature review, synthesizing theoretical and empirical research on public transport crowding, headway reliability, and network design. Chapter 3 details the methodology, including data sources, feature derivation, and the panel-data ordinal regression framework. Chapter 4 describes the case study context, outlining the operational characteristics of the bus and tram network under analysis and the specific corridor segments examined as well as showing detailed KPIs and statistical description of the analyzed data. Chapter 5 reports the empirical results, quantifying the effects of headway variability and line overlap on passenger comfort levels. Chapter 6 discusses these findings in light of existing theory and practice, exploring implications for public transport planning and potential strategies to mitigate crowding. Finally, Chapter **??** concludes by summarizing the key contributions, acknowledging limitations, and proposing avenues for future research. An overview of the report structure is depicted in Figure 1.4.1.

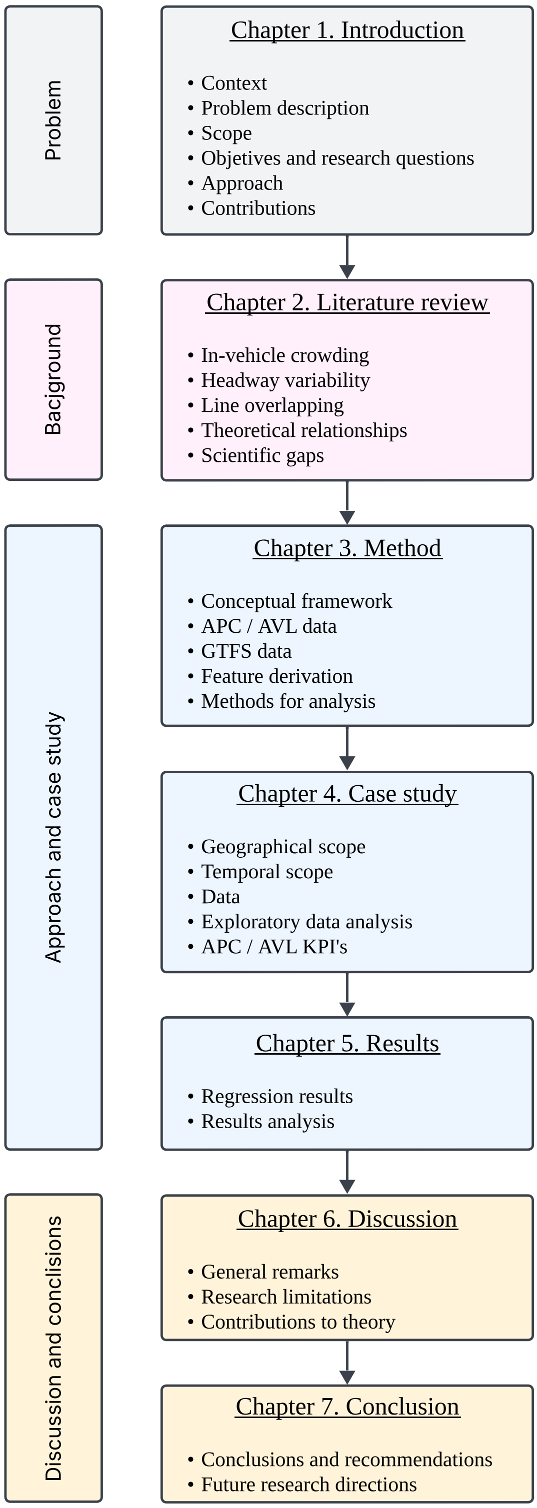


Figure 1.4.1: Report structure

Chapter 2

Literature review

2.1. Introduction

The relationship between in-vehicle crowding and headway variability in public transportation is a complex dynamic that has far-reaching impacts on passenger experience and system reliability. Public transport systems face ongoing challenges in managing the flow of passengers and maintaining consistent service, particularly in high-demand urban areas where small disruptions can lead to compounding delays (Daganzo, 2009). Crowding and headway variability are core issues within this domain, as both can create a cycle of service degradation that affects operational efficiency and passenger satisfaction. Understanding how these two elements interact is essential to developing effective strategies for improved public transport performance.

In-vehicle crowding affects not only passenger comfort but also public transport operations. When a bus or train becomes overcrowded, dwell times at each stop increase due to the extended time needed for boarding and alighting (Tirachini et al., 2022). This can lead to delays that cascade throughout the network, causing certain vehicles to fall behind schedule while others, with lighter loads, move ahead, exacerbating gaps in service (Ding & Chien, 2001; Muñoz et al., 2020; Drabicki et al., 2023). Conversely, when headway variability is high, meaning the intervals between consecutive vehicles are inconsistent, passengers are unevenly distributed, leading to packed vehicles and underutilized ones on the same route. This uneven distribution can trigger a negative feedback loop, where crowded vehicles lag further behind, and less crowded ones catch up, resulting in **bus or train bunching** (Daganzo, 2009; Godachevich & Tirachini, 2021). Bus bunching not only worsens crowding on certain vehicles but also creates uncertainty in passenger wait times, which can deter people from using the service.

Enhancing crowding models to better account for the impact of headway variability and line overlapping is an area of active research. Traditional models often assume uniform passenger arrival and demand (Lin & Ruan, 2009), but real-world conditions vary significantly due to factors like peak hours, special events, or even weather conditions. By incorporating headway variability into these models, public transport operators can more accurately predict crowding patterns and adjust services accordingly (Chen & Liu, 2011).

Line overlapping and passenger choice also play crucial roles in how crowding and headway variability manifest in a network. Line overlapping occurs when two or more routes share the same physical corridor for one or more consecutive stops. On the one hand, overlapping can improve perceived service frequency and offer passengers more route choices; on the other hand, it introduces a layer of operational complexity that can amplify headway variability. When multiple services compete for the same roadway segment, a delay on any one route propagates immediately to the others: a late vehicle on Route A forces subsequent vehicles of Route B to slow down or bunch, creating uneven intervals that cascade through the network. Similarly, any attempt to recover schedule adherence, for example, by holding back an early vehicle, must be coordinated across all overlapping lines, which is both technically challenging and potentially counterproductive if not perfectly timed. As a result, overlapping corridors tend to exhibit higher variance in both scheduled versus actual headways and in the incidence of bunching events (Diab et al., 2015).

When passengers have real-time information on crowding levels across routes, they are more likely to choose the less crowded options, helping to balance demand across the network (Drabicki et al., 2023). For operators to provide passengers with accurate and reliable data, Automatic Vehicle Location (AVL) and Automatic Passenger Count (APC) technologies offer valuable outputs for monitoring and managing crowding and headway variability (TRB, 2020b). AVL systems track vehicle locations, providing real-time insights into headways, which allows public transport agencies to detect irregularities like bus bunching or gaps in service. Meanwhile, APC systems capture precise boarding and alighting data, giving a detailed view of passenger load distribution across stops and routes. Together, AVL and APC data provide a comprehensive view of network conditions, enabling public transport agencies to not only respond to immediate operational issues but also plan strategically to improve service reliability and efficiency over time (Figliozzi et al., 2012).

Ultimately, the relationship between in-vehicle crowding and headway variability is a crucial area for public transport research and policy, as addressing these factors can lead to a more reliable, comfortable, and efficient public transport system. As cities continue to grow and demand for public transport rises, understanding and managing these dynamics will be essential for ensuring that public transport remains a viable and attractive option for urban mobility.

2.2. In-vehicle crowding

The phenomenon of crowding in public transport encompasses a range of qualitative factors that significantly influence the overall travel experience. Traditionally, the assessment of travel behavior has focused on time and cost as primary determinants of modal choice. However, contemporary research has highlighted the growing importance of qualitative attributes, such as comfort and convenience, particularly as the income levels of populations increase. Among these qualitative factors, the density of passengers , known as crowding, has emerged as a critical aspect that affects both the supply and demand dynamics of public transport systems.

Crowding in public transport is not merely a matter of physical discomfort due to limited space; it also involves various psychological, social, and health-related issues. High passenger density can lead to increased stress, anxiety, and a perceived invasion of privacy, all of which contribute to a negative travel experience (Batarce et al., 2016). Moreover, crowding can affect perceptions of safety and security, further influencing passengers' satisfaction and their likelihood to use public transport (S. Yan et al., 2021). As such, understanding the causes and effects of crowding, as well as developing effective methods for measuring it, is essential for improving public transport services and enhancing passenger welfare.

This section offers an extended analysis of the theoretical and applied aspects of in-vehicle crowding, considering operational variables, passenger behavior, and the intricate causal factors involved.

2.2.1. Measuring and Quantifying Crowding

Effective crowding measurement is pivotal for public transport agencies to design responsive interventions. Traditional metrics like Load Factor (LF), calculated as the ratio of passengers to seats, can misrepresent crowding due to their dependence on vehicle design and passenger distribution within vehicles. Multiple authors including, Fedujwar and Agarwal (2024) and Tirachini et al. (2016) suggest as a more standardized measure, Standee Density (SD) defined as the number of standing passengers per square meter, that addresses these design limitations and offers a more comparable metric across diverse vehicle types.

However, SD and LF overlook an essential dimension: passenger perception. As Fedujwar and Agarwal (2024) mention, crowding perception is a subjective construct shaped by psychological factors and contextual cues, such as duration of travel, vehicle type, and passengers' prior experiences. Studies suggest that even when SD remains constant, crowding can be perceived differently under varying conditions. This highlights the need for public transport systems to integrate passenger feedback and design crowding metrics that capture both objective density measures and subjective experiences.

2.2.2. Causes of Crowding

Crowding results from a complex interplay of supply-demand imbalances, operational factors, and external disruptions. High demand during peak hours remains a primary contributor to crowding as mentioned by Mahmoudi et al. (2023) and Tirachini et al. (2013). Limited service capacity and infrequent schedules exacerbate this demand, especially in metropolitan areas with significant commuter populations. Moreover, vehicle availability and infrastructure constraints may limit public transport authorities' ability to meet demand spikes.

Soza-Parra et al. (2021) and Tirachini et al. (2022) point out that beyond inherent demand-supply gaps, external disruptions like traffic congestion and incidents disrupt service regularity, leading to uneven passenger loads and intensified crowding. Operational decisions, such as driver adherence to scheduled headways, significantly impact service reliability. Deviations from planned schedules amplify the variability in vehicle arrival times, contributing to bus bunching. To counter this, real-time interventions, such as holding buses at strategic stops, can help maintain headway consistency and improve crowding distribution (Martínez-Estupiñan et al., 2023).

2.2.3. Consequences of Crowding Beyond Passenger Discomfort

While passenger discomfort is the most immediate outcome, crowding extends its impact to broader system performance. Crowded conditions increase dwell times, as passengers require more time to board and alight. This delay disrupts headway regularity, resulting in an unpredictable and prolonged travel experience (Figliozzi et al., 2012). Additionally, crowding poses safety concerns, particularly during peak times if and when vehicle capacities are exceeded. This exacerbates the risk of accidents, sudden stops, or fall hazards within vehicles (Tirachini et al., 2016).

Crowding-induced inefficiencies can create a negative feedback loop. Delays from crowding reduce operational efficiency, increasing the likelihood of service irregularities that lead to further crowding. Recognizing this, (Figliozzi et al., 2012) emphasize the necessity of crowding mitigation measures that also target these cascading effects on operational performance.

2.2.4. Interplay of Crowding with System Variables

Crowding operates in tandem with various system parameters, including headway variability, network design, and route configurations. Headway variability emerges as a critical factor. According to Daganzo (2009), Godachevich and Tirachini (2021) and Muñoz et al. (2020) this variability fosters a cyclical problem; as headway irregularities lead to crowding on specific vehicles, the ensuing delays disrupt the entire schedule, worsening headway adherence. Real-time monitoring systems and interventions, such as Automatic Vehicle Location (AVL) and Automatic Passenger Counting (APC) systems, can provide granular data to diagnose causes of headway variability and identify patterns contributing to bus bunching.

Line overlapping, while offering potential relief, requires careful consideration. The effectiveness of parallel routes in reducing crowding depends on passenger awareness of crowding levels on alternative options, highlighting the importance of real-time information dissemination (Drabicki et al., 2021, 2023; Soza-Parra et al., 2019). Godachevich and Tirachini (2021) delves into the trade-offs associated with route length and the impact of long routes on headway variability and crowding, suggesting the need for optimal route length determination.

Network configuration, including stop spacing and route design, further affects crowding. While longer routes might simplify network design, they are more susceptible to headway disruption due to higher variability in travel time. In contrast, optimized stop spacing and route segmentation strategies reduce dwell times and help maintain regular headways, ultimately mitigating crowding. Figliozzi et al. (2012) and Lin and Ruan (2009) discuss the utilization of AVL and APC data to analyze bus bunching occurrences, identify causes, and evaluate spatial and temporal patterns. This data-driven approach is essential for understanding crowding dynamics and developing targeted mitigation strategies.

2.2.5. Policy Interventions

To address in-vehicle crowding, public transport agencies globally employ a range of policy interventions. According to Mahmoudi et al. (2023) and Tirachini et al. (2016) enhancing service capacity during peak hours, through deploying larger vehicles or increasing trip frequencies, is a primary approach. Furthermore, holding control strategies, public transport signal prioritization, and optimized stop spacing have proven effective in reducing delays and improving headway adherence.

Optimizing operational efficiency is crucial for minimizing delays and maintaining service regularity. Holding control strategies, public transport signal priority, and optimized stop spacing are all identified as effective approaches (Soza-Parra et al., 2021; Tirachini et al., 2022). These operational interventions aim to break the negative feedback loop between crowding and headway variability, ensuring a smoother and more predictable service.

Demand management strategies focus on influencing passenger behavior to distribute demand more evenly. Drabicki et al. (2021) and (Fedujwar & Agarwal, 2024) mention how real-time crowding information, disseminated through apps or displays at stops, empowers passengers to make informed choices, potentially reducing peak crowding and improving the overall passenger experience.

Incorporating crowding costs into transport project appraisal guidelines is gaining traction, acknowledging the disutility associated with crowding and its impact on passenger welfare. Australia, France, Sweden, and the United Kingdom are examples of countries employing crowding multipliers, assigning higher values to travel time spent standing (Mahmoudi et al., 2023; Tirachini et al., 2016). This approach ensures that crowding considerations are integrated into planning and investment decisions, promoting a more holistic evaluation of transport projects.

In conclusion, analyzing the multifaceted nature of in-vehicle crowding, requires a balanced approach, integrating operational adjustments, real-time monitoring, policy interventions, and technological innovations. By addressing both the objective and perceived aspects of crowding, public transport agencies can enhance passenger experience and operational efficiency while reducing the broader impacts of crowding across public transport networks.

2.3. Headway Variability

Headway variability remains one of the most critical challenges in public transportation, affecting reliability, operational efficiency, and passenger satisfaction. As a key determinant of service predictability, headway variability directly influences the attractiveness of public transport systems by shaping the passenger experience and the perception of reliability (Figliozzi et al. (2012),TRB (2020a)). This section examines the core aspects of headway variability, including its measurement, underlying causes, operational impacts, relationships with other system variables, and policy interventions.

2.3.1. Measuring Headway Variability

Quantifying headway variability is complex, due to the intricate nature of public transport operations. To effectively measure headway irregularity, public transport agencies use several metrics, each offering unique insights into service consistency and reliability. The **standard deviation of observed headways** (σ_h) is a fundamental metric, capturing the degree of variation in headway times around the mean. This metric is simple and widely used to obteain the average waiting times at stops, but has limitations; it fails to account for deviations from the scheduled timetable, which means it may not fully reflect the service reliability expected by passengers (Godachevich & Tirachini, 2021). It is defined as

$$STD(h^{obs}) = \sqrt{\frac{\sum_{i=1}^{N}(h_i^{obs} - \overline{h^{obs}})^2}{N}} \tag{2.3.1}$$

where h_i^{obs} is the observed headway between buses i and $i+1$, $\overline{h^{obs}}$ is the average bus headway and N is the total number of headways observed.

A more sophisticated approach is the **Index per Observation (IPO)**, which compares observed headways with scheduled ones by applying a Box-Cox transformation. This metric provides a nuanced evaluation of both the variability and adherence to the timetable, thus enabling public transport agencies to assess how well actual service aligns with planned schedules. (Godachevich & Tirachini, 2021). It is defined as:

$$IPO = \frac{\sum_{i=1}^{N}(\frac{h^{obs}}{h_{sch}})^2}{N} \tag{2.3.2}$$

It depends on the observed headway (h^{obs}), scheduled headway (h_{sch}), and number of observations made (N)

Minutes of Incidence (M_{inc}) is another measure used to monitor deviations, particularly in public transport systems that operate under contractual or regulatory frameworks. M_{inc} penalizes headways that exceed a set threshold, which makes it relatively straightforward to implement. However, this measure tends to overlook broader variance patterns and does not fully capture the passenger experience, especially as it focuses more on regulatory compliance than on enhancing service quality (Godachevich & Tirachini, 2021).

As mentioned by Soza-Parra et al. (2022), the **coefficient of variation of headways (CV_h)** offers a dimensionless measure that adjusts headway dispersion relative to the average frequency. By providing context on how headway variability changes with service frequency, CV_h enables public transport agencies to compare different routes or service types, such as high-frequency urban lines and lower-frequency suburban routes. The CV_h has a relation to the IPO given by

$$IPO = CV^2 + 1 \tag{2.3.3}$$

Excess wait time is another valuable metric, particularly for passenger-centered analyses, as it measures the additional waiting time passengers incur due to irregular headways, directly linking operational variability to passenger dissatisfaction (TRB, 2020a).

Finally, **percentile-based headway values**, such as the 95th percentile, help capture extreme cases of irregularity that affect passengers most. This metric identifies headway outliers, such as long delays, providing insights into the upper bounds of wait times experienced by passengers and allowing public transport agencies to address severe irregularities more effectively (TRB, 2020a).

Each of these measures, while valuable on its own, is often used in combination to provide a comprehensive view of headway variability in complex public transport systems.

2.3.2. Causes of Headway Variability

Headway variability arises from a complex set of factors, both within and outside the public transport system. One primary contributor is irregular dispatching at terminals, where inconsistencies in dispatch intervals, due to issues like driver availability, vehicle readiness, and terminal congestion, can trigger a cascade of delays along the route. In the the researches by Godachevich and Tirachini (2021), Soza-Parra et al. (2021) and Tirachini et al. (2022) it is highlighted that even minor deviations in terminal dispatch can propagate through the entire service, significantly affecting headway regularity.

Another major factor is the scheduled frequency of service, as high frequencies, though beneficial for passengers, create operational challenges in maintaining consistent headways. Short intervals between buses allow less buffer time for adjustments, meaning that even small delays can result in significant variability across the service. According to Figliozzi et al. (2012), high-frequency public transport services require real-time adjustments and advanced operational controls to correct minor disruptions before they escalate and propagate.

In their research, Figliozzi et al. (2012) also mention that the route distance and complexity further impact headway variability. Longer routes, particularly those that traverse dense urban areas, are more prone to cumulative delays from traffic congestion, incidents, and variations in boarding and alighting patterns. Studies using Automatic Vehicle Location (AVL) data show that longer routes tend to exhibit greater headway variability due to prolonged exposure to potential disruptions.

Passenger demand fluctuations and variable dwell times at stops are also significant causes of headway variability. Unpredictable demand levels, combined with varied boarding and alighting times, disrupt headway consistency by creating delays at stops. Routes with highly variable demand, such as those serving event venues, schools, or commercial areas, are particularly vulnerable to these disruptions (Martínez-Estupiñan et al., 2023).

External factors such as traffic conditions and right-of-way availability also impact headway variability. Congestion, traffic incidents, and the absence of dedicated public transport lanes often result in inconsistent travel times, which directly affect headway regularity. Dedicated infrastructure like bus-only lanes and signal priority measures can help mitigate these effects, providing a more predictable operating environment for public transport vehicles ((Y. Yan et al., 2016; Figliozzi et al., 2012)).

2.3.3. Explanatory Variables for Headway Variability

Headway variability, the inconsistency in the intervals between successive public transport vehicles, is a major contributor to service unreliability, vehicle bunching, and in-vehicle crowding. Drawing on the synthesis provided by Tirachini et al. (2022), several key determinants emerge, each influencing the degree to which scheduled service intervals are maintained in real-world operations.

Initial Headway Irregularities at Dispatch. One of the most critical moments for ensuring headway regularity occurs at vehicle dispatch. Variability introduced at this early stage often propagates downstream. Contributing factors include route characteristics (length, average passenger demand, scheduled frequency, and expected travel speed), terminal and depot logistics (such as circulation complexity and depot proximity), and the practices of individual operators. For instance, inconsistent driver availability due to absenteeism can disrupt scheduled dispatches. The absence of effective control mechanisms at the terminal may result in large deviations that only worsen along the route.

Scheduled Frequency. High-frequency services, while attractive for reducing passenger waiting times, are inherently more susceptible to bunching. As scheduled headways shorten, the system becomes increasingly sensitive to minor delays that disrupt spacing. Thus, operational plans must balance frequency benefits with the increased risk of instability in inter-vehicle timing.

Distance Travelled Along the Route. The further a vehicle travels from its origin, the more exposed it becomes to random sources of delay, such as fluctuations in boarding demand, traffic congestion, or road incidents. These cumulative disruptions make it increasingly difficult to preserve regular headways without active control strategies. Empirical evidence confirms that headway irregularities tend to grow with distance traveled, especially in the absence of holding or dispatching corrections.

Passenger Demand and Dwell Time Variability. Higher passenger demand directly contributes to increased headway variability through its impact on dwell time. As more passengers board and alight, especially during peak periods or under crowded conditions, dwell times increase and become less predictable. Operational practices also matter: systems that use off-board fare collection or allow all-door boarding reduce dwell time variability, while onboard payment systems or the need to operate wheelchair lifts increase it substantially.

Traffic Conditions and Right-of-Way Design. Traffic congestion and incidents are key drivers of travel time variability and, by extension, headway irregularity. Bus lanes or fully segregated rights-of-way can mitigate these effects, but shared lanes, especially those allowing turning vehicles, do not necessarily improve regularity. Hence, the degree of physical separation from general traffic is a critical determinant of operational stability.

Traffic Signals Downstream of Stops. Signalized intersections can introduce substantial and unpredictable delays between stops. While the presence of signals generally increases travel time variability, their impact on headway regularity can be mitigated with technologies such as public transport signal priority (TSP), especially when configured to adjust dynamically based on actual headway deviations rather than static schedules.

Driver Behavior and Institutional Practices. Finally, the performance and behavior of drivers also matter. Experienced and well-supported drivers are more likely to maintain consistent operating speeds and comply with headway management instructions. Organizational factors such as vehicle condition, scheduling flexibility, and the responsiveness of operations staff further shape the likelihood of successful headway control.

To complement the qualitative discussion above, Table 2.3.1 presents a synthesized overview of operational, infrastructural, and behavioral variables identified in the literature as significant determinants of headway variability. The strength of influence is expressed qualitatively based on the evidence presented in multiple empirical studies. A "+" symbol indicates a weak-to-moderate effect, while "+++" signals a strong influence on the disruption of scheduled vehicle intervals.

Variable	**Likely Overall Influence**
Headway variability at route origin	+++
Scheduled frequency	+++
Distance travelled from origin	++ / +++
Passenger demand	++
Number of stops	++
Off-board payment stops	++
Right of way design	+ / ++
Congestion	+ / ++
Traffic signals	+ / ++
Incidents	+ / ++
Driver behavior or experience	+
Fleet type (vehicle heterogeneity)	+

Table 2.3.1: Summary of Key Factors Influencing Headway Variability (summarized from Tirachini et al. (2022))

In summary, headway variability is a complex, multifactorial issue driven by both controllable and uncontrollable elements. Effective mitigation requires coordinated attention to upstream dispatching, mid-route control strategies, network design, and operator performance, each of which plays a crucial role in determining the passenger experience and the operational efficiency of the public transport system.

2.3.4. *Consequences of Headway Variability*

The consequences of headway variability extend well beyond operational metrics, affecting both passenger experience and system efficiency. Irregular headways lead to increased waiting times for passengers, as the unpredictability of service intervals reduces reliability and undermines passenger confidence. According to studies by Muñoz et al. (2020) and Fedujwar and Agarwal (2024), passengers experiencing longer and uncertain wait periods report higher perceived wait times, which can decrease satisfaction and ultimately reduce ridership.

Bus bunching, where buses on the same route cluster together and are followed by long service gaps, is another result of headway variability. As described by Chen and Liu (2011), Figliozzi et al. (2012), TRB (2020a) and others, this bunching not only leads to overcrowded vehicles, delaying boarding and alighting, but also reduces capacity utilization efficiency. The discomfort and inconvenience associated with bus bunching create a cycle of inefficiency that impacts both passengers and operators. When bunching happens, the majority of passengers experience reduced service quality, since more passengers travel in crowded vehicles than empty ones.

Furthermore, fluctuating headways undermine the reliability and predictability of public transport service, making it difficult for passengers to plan trips accurately. This erosion of confidence can lead to a modal shift from public transport to private vehicles, reducing the social and environmental benefits associated with public transportation. Financially, the unpredictability of headways necessitates additional resources to maintain service levels, leading to increased operational costs (Y. Yan et al., 2016; Tirachini et al., 2013).

2.3.5. *Interaction with System Variables*

Headway variability dynamically interacts with various system variables, creating interdependent challenges within the public transport network. For example, headway variability often increases in-vehicle crowding, as irregular intervals lead to uneven passenger loads. According to Fedujwar and Agarwal (2024), Chen and Liu (2011) and Mahmoudi et al. (2023), this effect can create a feedback loop in which crowded buses experience longer dwell times, worsening headway irregularity. This interaction suggests that improvements in headway management can positively impact crowding and vice versa.

Another factor affected by headway variability is line overlapping. Overlapping or parallel routes can provide passengers with alternative travel options, potentially mitigating the negative effects of headway variability and crowding on a single line. However, as noted by Fedujwar and Agarwal (2024), the effectiveness of this approach depends on real-time information systems that keep passengers informed about crowding levels on alternative routes.

Network configuration, including route design, stop spacing, and infrastructure availability, also influences headway regularity. Dedicated lanes, optimally spaced stops, and simplified route designs can reduce dwell times and travel time variability, supporting more consistent headways. Systems with long routes and frequent stops tend to exhibit higher headway variability, indicating that route and stop configuration require careful optimization to balance operational efficiency with accessibility Lin and Ruan (2009).

2.3.6. *Policies to Reduce Headway Variability*

To mitigate headway variability, public transport agencies employ a range of policies and operational strategies. Holding control is a widely used approach in which buses are held at designated stops to regulate headways. Supported by AVL systems, this strategy has proven effective in reducing bus bunching and maintaining predictable service intervals (Daganzo, 2009; TRB, 2020a). However, holding requires precise calibration to avoid excessive passenger delays, ensuring a balance between headway regularity and travel time.

Transit Signal Priority (TSP) systems, which give priority to buses at traffic signals, also help reduce travel time variability by minimizing delays at intersections. As highlighted by TRB (2020a), TSP systems are particularly useful in urban areas where signal-induced delays are a primary cause of headway irregularity, allowing dynamic adjustments to signal timings that prioritize buses.

Optimized stop spacing is another effective approach. By strategically placing stops based on demand and operational efficiency, public transport agencies can regulate dwell times more effectively, minimizing disruptions to headways. This strategic placement enhances accessibility and operational performance, providing a balanced approach to supporting consistent headways (TRB, 2020a).

Real-time information dissemination enhances the public transport experience by keeping passengers informed of bus arrival times and headway status, thereby empowering passengers to make informed travel decisions. Studies by Drabicki et al. (2023) and Drabicki et al. (2021) suggest that this measure is particularly effective when combined with mobile applications and digital displays.

Driver training and consistency programs also play a critical role in reducing driver-induced headway variability. Programs that emphasize steady driving speeds and adherence to schedules contribute to smoother, more predictable service. According to Godachevich and Tirachini (2021), these programs are especially relevant in public transport systems where variability often results from operator behavior.

2.4. Line Overlapping

Line overlapping refers to the condition in which two or more public transport routes share a portion of their sequence of stops. While this configuration can enhance service frequency in the shared segments and provide greater route flexibility, it also introduces significant operational complexities. In high-frequency public transport systems, overlapping routes have been consistently linked to operational instability. The following sections synthesize empirical evidence and mechanistic insights from the literature regarding the relationship between overlapping routes and in-vehicle crowding.

2.4.1. *Overlapping Routes Exacerbate In-Vehicle Crowding*

Several studies explicitly link line overlapping to operational dynamics that lead to worsened crowding conditions. For instance, Diab et al. (2015) directly investigates the impacts of overlapping bus service on headway delays and bus bunching two critical precursors to increased crowding, and concludes that service overlapping does increases the headway delay and therefore increases the passengers' waiting times

Similarly, Iliopoulou et al. (2020) provides clear empirical evidence that routes operating on shared corridors experience more frequent instances of bus bunching. By applying headway deviation analysis and spatio-temporal clustering techniques, their study distinguishes the patterns of bunching according to route characteristics, revealing that overlapping corridors exhibit higher intensities of disruption. The resulting bus bunching leads to imbalanced vehicle loading, with some buses becoming significantly more crowded than others.

Furthermore, Arriagada et al. (2019) employs GPS and Automatic Fare Collection (AFC) data to examine factors driving bus bunching in cities such as Santiago and Gatineau. Their findings indicate that high scheduled frequencies, irregular dispatch headways, and shared route segments (referred to as "common-route services") collectively contribute to increased bunching. Since bunching results in highly variable passenger loads across vehicles, this study reinforces the direct connection between line overlapping and in-vehicle crowding.

2.4.2. Dynamics between overlapping and crowding

The reviewed literature identifies several mechanisms through which line overlapping exacerbates in-vehicle crowding:

Amplification of Headway Irregularities

Studies such as Diab et al. (2015), Iliopoulou et al. (2020), and Arriagada et al. (2019) demonstrate that overlapping corridors lead to inter-line interference and irregular dispatching, which in turn increases headway variance. Foundational research by Strathman et al. (n.d.) and Figliozzi et al. (2012) establishes that longer or irregular headways directly contribute to higher passenger accumulation at stops. This accumulation causes subsequent vehicles to experience extended dwell times and increased crowding, as they must accommodate a larger influx of boarding passengers.

Bunching Hotspots in Shared Sections

Empirical evidence from Iliopoulou et al. (2020) indicates that the spatio-temporal clustering of bunching events is particularly concentrated in shared corridor segments. In instances of bus bunching, the first vehicle in a bunch often becomes overloaded and experiences prolonged dwell times, while following vehicles may remain underutilized. This dynamic of uneven load distribution directly contributes to in-vehicle crowding.

Competition Across Lines

Although not explicitly framed as competition, both Diab et al. (2015) and Arriagada et al. (2019) report that routes sharing corridor segments suffer from increased operational instability. When multiple lines operate within the same corridor without coordinated scheduling, the resulting uncoordinated operations lead to amplified passenger surges and uneven load distributions, thereby exacerbating crowding. Additionally, as discussed by Feng and Figliozzi (2011) and Tirachini et al. (2022), the feedback loop wherein crowding induces delays, and delays subsequently cause further crowding, further compounds the issue.

2.4.3. Relevance to In-Vehicle Crowding

The collective findings from the reviewed studies establish clear operational relationships between line overlapping, headway deviations, and bus bunching, which in turn directly impact in-vehicle crowding through several pathways:

- **Overlapping routes** → Greater headway variability → Increased passenger accumulation at stops → Uneven boarding across vehicles → In-vehicle crowding.
- **Overlapping routes** → More severe bunching events → Overloading of the first bus in the bunch → Increased onboard crowding.
- **Shared corridors** → Uncoordinated operations across multiple lines → Amplified passenger surges → Overcrowded vehicles.

It is important to note that while these studies provide robust observational evidence linking overlapping routes to in-vehicle crowding, none offers a quantitative model that explicitly estimates the increase in crowding as a function of overlapping. The evidence remains primarily observational and correlative rather than derived from experimental or fully causal econometric analyses. Nonetheless, the convergence of findings across multiple sources underscores the significance of line overlapping as a critical factor in understanding and mitigating in-vehicle crowding in high-frequency, high-demand public transport systems.

2.5. Relationship Between Crowding, Headway, and Overlapping

Understanding the theoretical interplay among in-vehicle crowding, headway variability, and line overlapping is fundamental to improving public transport system performance. This section synthesizes the relevant literature and presents a conceptual framework that explains how these factors interrelate.

2.5.1. *Headway Variability as a Driver of Crowding*

Theoretical models of public transportation have long emphasized that regular headways are crucial for maintaining uniform passenger loads across vehicles. When headways become irregular, due to fluctuations in traffic conditions, passenger boarding times, or other disruptions, the system experiences *vehicle bunching*. In such scenarios, one bus may accumulate a high number of waiting passengers, while subsequent buses may arrive relatively empty. This uneven distribution results in higher in-vehicle crowding for the first bus in the bunch, which is exacerbated by increased dwell times and delayed departures (Chen & Liu, 2011; Tirachini et al., 2016).

2.5.2. *The Role of Line Overlapping in Operational Dynamics*

While overlapping routes can enhance service frequency and offer flexible travel options, they also introduce operational complexities that affect headway stability. In a shared corridor, vehicles from different lines interact, and their schedules may not be perfectly coordinated. This inter-line interference can lead to irregular dispatch intervals and increased variability in headways, thus compounding the risk of vehicle bunching (Iliopoulou et al., 2020; Diab et al., 2015). Moreover, overlapping routes can create *competition* for boarding passengers, especially at shared stops. This competition intensifies during peak periods, where even small deviations in headways can cause significant imbalances in passenger loads across vehicles.

2.5.3. *Integrated Dynamics: Feedback Loops and Amplification Effects*

The theoretical framework linking these factors can be conceptualized as a series of interconnected feedback loops:

1. **Headway Variability and Passenger Accumulation:** Irregular headways cause inconsistent intervals between vehicles, leading to the accumulation of passengers at stops. When a bus finally arrives, it must accommodate a larger-than-average number of boarding passengers, which in turn increases dwell time. Longer dwell times can then trigger further deviations from the scheduled headway, perpetuating the cycle of irregular service.

2. **Line Overlapping as an Amplifier:** In corridors where multiple lines overlap, the impact of headway variability is amplified. Shared routes complicate the scheduling process, as vehicles from different lines are likely to interfere with one another's timing. This interference increases the frequency and severity of headway deviations, thereby exacerbating the phenomenon of bus bunching. The resulting imbalances in passenger loads are more pronounced, leading to heightened levels of in-vehicle crowding.

3. **Combined Impact on In-Vehicle Crowding:** The combination of irregular headways and overlapping routes creates a compounded effect on crowding. First, irregular headways lead to passenger surges and bunching. Second, the operational challenges introduced by overlapping, such as uncoordinated dispatching and competition for boarding, intensify these surges. The net result is a system in which vehicles experience significantly uneven load distributions, with certain vehicles becoming severely overcrowded while others remain underutilized.

2.5.4. *Conceptual Model*

Figure 1.2 illustrates the conceptual model developed from the literature. The model depicts how headway variability directly leads to passenger accumulation and how overlapping routes amplify this effect by introducing additional variability and competition among vehicles. This integrated view helps explain the observed empirical patterns of in-vehicle crowding and provides a theoretical basis for the subsequent data-driven analysis presented in this thesis.

In summary, the theoretical relationship among in-vehicle crowding, headway variability, and line overlapping is characterized by a series of reinforcing feedback loops. Irregular headways directly contribute to crowding by causing passenger accumulation, while overlapping routes amplify these effects by introducing further operational complexity and inter-line interference. Together, these factors create a dynamic system where even minor deviations in service regularity can lead to significant variations in vehicle occupancy, thereby undermining overall service quality.

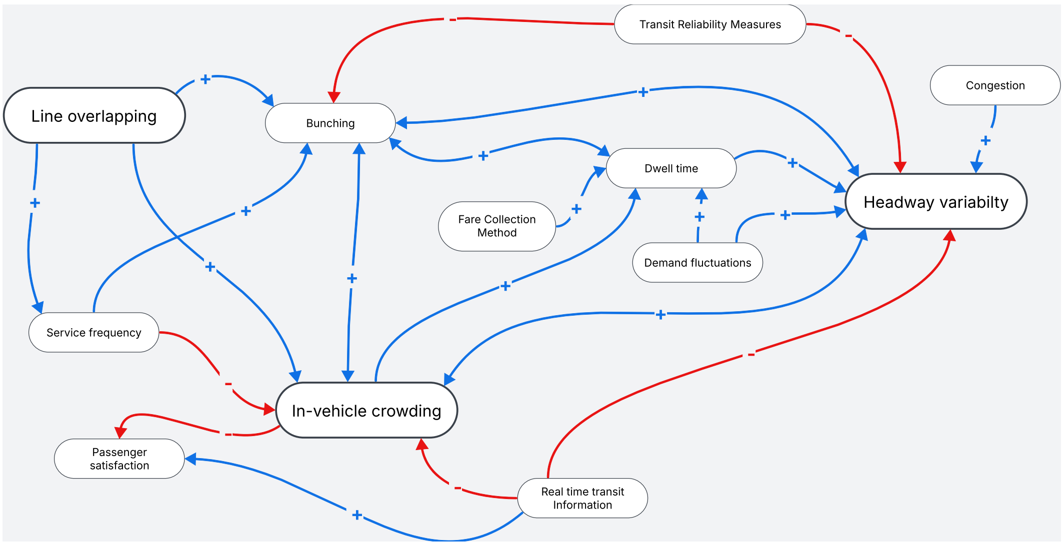


Figure 2.5.1: Conceptual model of the relations between Crowding, Headway, and Overlapping

2.6. Chapter Conclusion

This chapter has provided a comprehensive review of the literature and theoretical foundations underlying the relationships between in-vehicle crowding, headway variability, and line overlapping. By synthesizing previous studies, we have established a conceptual framework that highlights the complex interdependencies among these factors.

2.6.1. Key Findings and Certainties

Several key insights can be confidently drawn from the chapter:

- **Headway variability is a primary driver of in-vehicle crowding.** The literature strongly supports the assertion that irregular headways lead to an uneven distribution of passengers across vehicles. When headways deviate from their intended schedule, certain vehicles experience significantly higher occupancy levels while others remain underutilized. This imbalance leads to excessive crowding, longer dwell times, and a deterioration in service reliability (Tirachini et al., 2016; Chen & Liu, 2011).
- **Line overlapping amplifies the negative effects of headway variability.** In corridors where multiple public transport lines share stops, coordination challenges arise, making it more difficult to maintain consistent headways. Inter-line interference can cause larger deviations from scheduled headways, further exacerbating crowding issues. Overlapping routes create additional uncertainty in service regularity, leading to unpredictable passenger distributions across vehicles (Diab et al., 2015; Iliopoulou et al., 2020).
- **The relationship among these factors is characterized by reinforcing feedback loops.** Once headway variability begins to manifest, it triggers a self-perpetuating cycle where uneven passenger loads cause increased dwell times, which in turn lead to further deviations from the schedule. When overlapping routes are present, this feedback loop intensifies, making it even more challenging for public transport operators to recover regular service intervals.

These findings confirm that managing headway variability and considering the impacts of network design are crucial for mitigating in-vehicle crowding and improving public transport service quality.

2.6.2. Unanswered Questions and Knowledge Gaps

Despite these established insights, several questions remain open, highlighting areas where further research is needed:

- **Quantifying the relationship between headway variability and crowding.** While it is well understood that headway irregularities increase crowding, precise quantitative models linking these two phenomena remain limited. Empirical studies using large-scale datasets, such as Automatic Vehicle Location (AVL) and Automatic Passenger Count (APC) data, could offer more concrete estimations of this relationship.

- **Understanding the network-wide impact of line overlapping.** Most existing studies focus on localized effects of overlapping routes rather than analyzing their system-wide implications. It remains unclear whether overlapping corridors always lead to increased crowding, or whether certain network designs can mitigate these negative effects.

Addressing these gaps will be essential for advancing both theoretical and practical understandings of public transport system performance.

Chapter 3

Methodology

3.1. Introduction

This chapter presents the methodological framework used to analyze how public transport service characteristics influence in-vehicle comfort across an urban transport network. Our objective is to model the relationship between operational variables, such as headway variability, service overlap, and bunching, and the comfort levels of passengers, which are reported as an ordinal variable ranging from 1 (least crowded) to 5 (most crowded).

The data structure reflects a fine-grained panel design. Each observation corresponds to a vehicle stop event defined by its stop location, line-direction, and service day. For each stop-day-line combination, we chronologically order the vehicles that serve that stop using a trip sequence variable. This structure allows us to capture the evolution of service patterns at each physical stop over the course of a day.

Passenger comfort is treated as an ordinal outcome, and we estimate a random-effects ordered logistic regression model. This specification is well-suited to our context because it accommodates unobserved heterogeneity across stop-day-line clusters while maintaining interpretability of the ordinal structure. Fixed-effects estimators for ordered logit models are not feasible due to the incidental parameters problem: introducing a large number of cluster-specific intercepts leads to inconsistent and biased estimates of the slope coefficients when the number of time observations is limited per cluster (Hole et al., 2011).

The random-effects model instead assumes that cluster-specific intercepts are drawn from a common distribution and are uncorrelated with the predictors. While this assumption cannot be directly tested, it enables consistent estimation of both structural coefficients and the variance of unobserved heterogeneity, provided the exogeneity condition holds.

We detail the construction of key explanatory variables, including headway, bunching, cumulative line frequency, and network overlap, and describe their hypothesized relationship with crowding. We also include operational controls such as peak-hour flags and public transport mode dummies. This chapter proceeds by defining the panel structure and statistical model, explaining estimation procedures, and outlining the diagnostic steps used to validate the approach.

3.2. Input Data

In this section, we describe the two primary data sources underpinning our analysis: the combined Automated Passenger Counter and Automated Vehicle Locator (APC/AVL) feed provided by the operator, and the General Transit Feed Specification (GTFS) schedule data. We detail how each dataset was acquired, the available fields and their formats, and the preprocessing steps undertaken to render them analysis-ready. The fully harmonized dataset, resulting from a composite-key join of APC/AVL and GTFS records, is denoted as *events_analysis* and forms the basis for feature engineering and modeling.

3.2.1. APC/AVL Data

The Automated Passenger Counter (APC) and Automated Vehicle Locator (AVL) systems together form the primary source of observed operational and passenger load data. These systems are deployed by the public transport operator to monitor vehicle performance and passenger flow at a high temporal and spatial resolution. For this study, APC and AVL records have been integrated by the operator into a unified dataset that reports detailed stop-level information for every vehicle trip across the network. Each record in the dataset corresponds to a single stop event, a unique occurrence of a vehicle arriving at and departing from a specific stop as part of a scheduled trip. The data are organized chronologically within each trip and are enriched with both scheduled and actual departure times, allowing for the calculation of punctuality, headway deviations, and travel times. Moreover, vehicle characteristics and capacities are merged into the dataset using the vehicle ID as a linking key to the operator's fleet registry.

The accuracy of APC systems varies by sensing technology. Infrared-based systems, commonly installed in buses and trams, exhibit moderate baseline accuracy (approximately 77%) but can achieve 95–97% accuracy when a ± 1 passenger tolerance is permitted. Their performance is sensitive to factors such as crowding and sensor placement (Cavallero et al., 2023). Pressure-based systems, which infer passenger counts from weight changes, demonstrate strong accuracy for total onboard loads (1–4% relative error), though they struggle to differentiate boarding from alighting passengers (Cavallero et al., 2023). Finally, emerging Wi-Fi and cellular signal tracking methods can reach up to 79% accuracy, though they introduce biases related to multi-device users and undetectable passengers. These technological differences underscore the need for system-level calibration and tolerance-aware evaluation when applying APC data to operational analyses (Barabino et al., 2025). After the measurement, there is a post processing by the operator that smooths and calibrate the optputs.

Although Automatic Vehicle Location (AVL) systems are widely deployed in public transport networks to monitor service reliability, they do not always provide complete or fully representative data. Even when fleets are fully AVL-equipped, archived data often include anomalies, such as missing timestamps or erroneous positions, that can distort reliability analyses. Research by Barabino et al. (2017) has shown that neglecting these anomalies can lead to underestimation of headway variability and regularity issues, misrepresenting the service as experienced by passengers. According to Barabino et al. (2017) addressing AVL data anomalies significantly impacts headway-based reliability metrics where a 5% increase in missing data can lead to a corresponding 5% increase in measured headway variability; but has minimal effect on schedule-based punctuality measures that remain largely unchanged. This finding highlights the importance of targeted data validation for studies focusing on passenger-experienced service quality.

These APC/AVL records form the empirical foundation of the methodology. They not only support the derivation of the dependent crowding variable but also allow for the construction of key explanatory features, such as actual headway, bunching detection, and observed passenger loads. This high-resolution view of vehicle-stop interactions enables the application of panel-data modeling techniques, as each action of stopping is uniquely identified by its position within the trip, the trip ID, the stop ID, the date, and the route.

By combining real-time observations with scheduled expectations, the APC/AVL dataset provides a dynamic and operationally grounded view of public transport activity, essential for modeling the stochastic nature of passenger comfort and vehicle performance across space and time.

3.2.2. GTFS data

The GTFS static feed is a structured data format that provides detailed and standardized information about a public transport agency's fixed schedules, routes, stops, and other operational details. This feed is designed to be machine-readable, enabling developers, planners, and other stakeholders to analyze and integrate public transport information into various applications, such as trip planners, scheduling tools, and urban mobility platforms (GTFS.org, 2024).

At its core, the GTFS static feed comprises a collection of plain text files. Each file within the feed represents a specific aspect of the public transport system, such as stops, routes, trips, schedules, and fare information. For instance, the *stops.txt* file lists all public transport stops or stations, including their names, geographic coordinates, and IDs. Similarly, the *routes.txt* file outlines the public transport lines or services, their IDs, names, and types (e.g., bus, subway, train).

One of the most critical components is the *trips.txt* file, which links routes to scheduled services and defines individual trips along these routes. This file works in tandem with *stop_times.txt*, which specifies the exact times each trip is expected to arrive at and depart from the stops along its route. Together, these files provide a complete picture of the public transport agency's operations, from when and where vehicles operate to how passengers move through the system.

GTFS static also supports additional files to include information about fares, service exceptions in the *calendar_dates.txt*, and sometimes geographic shapes of routes (*shapes.txt*). These supplementary files enhance the richness of the data, allowing applications to provide more precise and comprehensive public transport information, such as calculating the cost of a trip or visualizing routes on a map.

This data format is particularly valuable because it is designed for global compatibility and is easy to integrate into a variety of tools and systems. Public transport agencies can provide GTFS feeds to make their services discoverable in popular trip planning platforms like Google Maps, while urban planners can use the data for modeling and analysis. By providing a consistent structure, the GTFS static feed bridges the gap between public transport providers and the public, fostering better accessibility and understanding of public transport systems.

The relationship schema of GTFS data is shown in Figure 3.2.1.

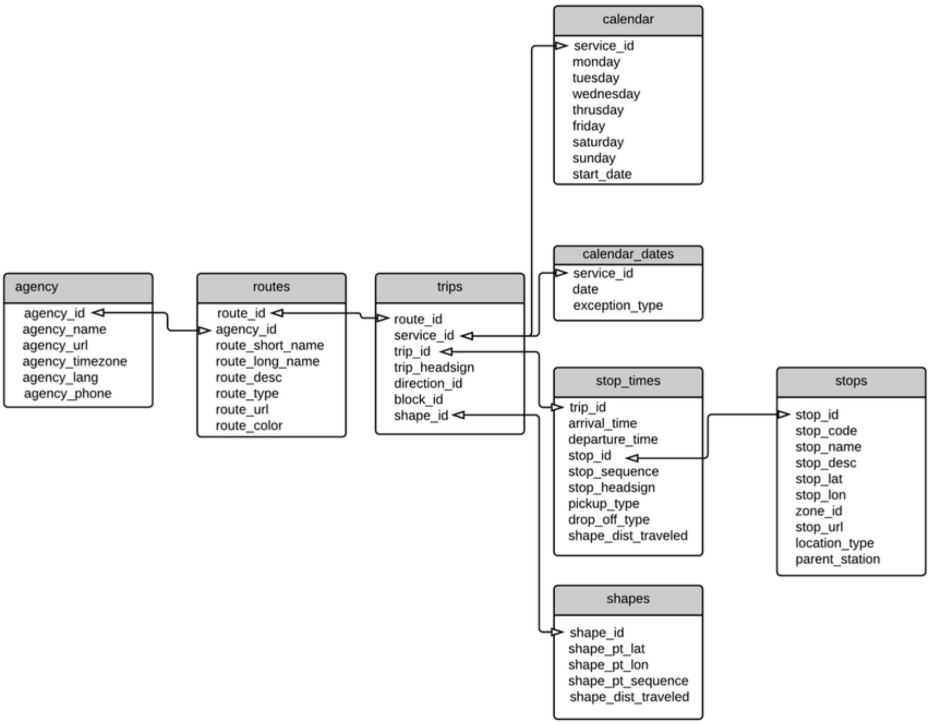


Figure 3.2.1: Relational structure of the GTFS datasets.

3.3. Pre-processing & Harmonization

Before any analysis can be conducted, the raw APC/AVL and GTFS feeds must undergo extensive cleaning, enrichment, and alignment to ensure that each stop-level record reflects a coherent, passenger-focused view of service performance. In this section, we describe the rationale and methods for each stage of pre-processing, emphasizing how these operations preserve the integrity of headway, punctuality, and crowding indicators.

3.3.1. APC/AVL Cleaning & Enrichment

The combined APC/AVL dataset contains real-time observations that are subject to sensor noise, clock drift, and vehicle-idiosyncratic conventions. First, we restrict the dataset to core service hours (05:00–20:00). overnight operations often follow different dispatching rules or rely on reduced service patterns; excluding these periods ensures that our analysis targets the main demand windows where crowding is most relevant while keeping the midday valley in the data.

Next,we truncate *terminal_time*, to the nearest minute by setting seconds to zero. This standardization aligns the high-precision AVL logs with the minute-resolution schedule data in GTFS, preventing misalignments.

We then assign a *trip_type* label to each event by grouping runs that share an identical sequence of stops. Some of the studied routes have scheduled branching or stop skipping; trip-type classification guarantees that only truly comparable runs are analyzed together, which is essential for robust headway and crowding calculations.

Additional metadata fields are computed to facilitate both modeling, interpretation and filtering. A *day_of_week* variable helps filter out weekends from the data, while a binary *peak_flag* indicates whether the departure occurs during the morning (07:00–09:00) or evening (16:00–19:00) rush periods. Finally, we perform a manual consistency check on each line to resolve anomalies such as dual-stop naming at border crossings or intentional loopbacks that revisit a stop; these cases are flagged or reconciled so that stop-sequence ordering remains consistent.

The integration of APC/AVL data with GTFS schedules is achieved through a multi-key join operation based on the date, terminal departure time, stop sequence, line-direction identifiers, and stop IDs. This allows for each observed stop-event to be matched with its corresponding planned context. Through this linkage, various operational indicators are derived, including expected and actual headways, bunching conditions, and metrics of line overlap. The latter include the number of lines serving the same arc, the cumulative frequency of those lines on an hourly basis, and a normalized index representing the proportion of shared arcs remaining after the current stop.

3.3.2. GTFS Filtering & Trip-Type Extraction

As mentioned, the GTFS static feed provides the operator's planned schedule. The information we accessed contained data for other several operators. To derive a baseline for the planned schedule we first filter *trips.txt* and *stop_times.txt* by the relevant operator, discarding any irrelevant data. We then intersect each trip's *service_id* with *calendar.txt* to retain only those trips active on the dates in our APC/AVL window. Next, we extract the same *trip_type* labels from the GTFS data by grouping trips that share both route, direction, and ordered stop sequences. By mirroring the APC/AVL classification, we guarantee a one-to-one correspondence between planned and observed runs, which is critical for accurately computing deviations.

Table 3.3.1 and Table 3.3.2 provide comprehensive schemas for the raw APC/AVL and GTFS inputs, respectively. Together, they document the column names, data types, and sources that feed a the harmonized table, ensuring full transparency and reproducibility of the pre-processing pipeline.

Variable	**Description**
Date	The date of the trip.
Stop Name	The name of the current stop.
Stop Sequence	The ordinal position of the stop within the trip.
Punctuality	The deviation in seconds between actual and scheduled departure at the stop.
Terminal Time	The scheduled departure time from the first stop of the trip.
Expected Departure	The scheduled departure time from the current stop
Actual Departure	The recorded departure time from the current stop, obtained from AVL.
Line Direction	The line number and direction; all lines operate bidirectionally (e.g., "17 – Aller").
Vehicle ID	The unique identifier of the vehicle performing the trip.
PT Mode	The vehicle model/type used, which determines its capacity.
Passengers On Board	The estimated number of passengers on board at the time of departure from the stop.
Passengers Alighting	The estimated number of passengers alighting at the stop.
Passengers Boarding	The estimated number of passengers boarding at the stop.
Weekday	Day of the week
Peak flag	1 if trip happens either 07:00–09:00 or 16:00–19:00, 0 else wise

Table 3.3.1: Description of trip realization data columns from APC and AVL systems (data provided by operator)

Variable	**Description**
Date	The date of the trip.
Trip ID	Unique daily ID for each trip
Stop ID	Unique stop identifier
Stop Name	The name of the current stop.
Stop Sequence	The ordinal position of the stop within the trip.
Trip headsign	Final destination of the trip
Departure time	The scheduled departure time from the each stop of the trip.
Terminal Time	The scheduled departure time from the first stop of the trip.
Line Direction	The line number and direction
PT Mode	Differentiates between, bus, tram, and trolleybus

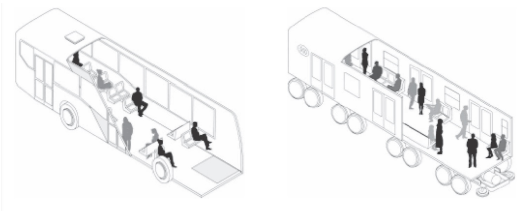
Table 3.3.2: Description of selected columns from GTFS feed

3.4. Variable Definition

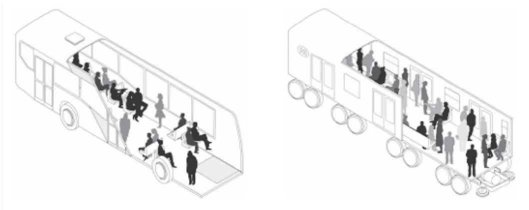
In this section, we present the construction of the dependent comfort index and the suite of predictor variables used to model crowding outcomes. Starting from the harmonized event table *events_analysis*, we first define the ordinal dependent variable and then detail the computation of each potential operational predictor.

3.4.1. Comfort Index (Target Variable)

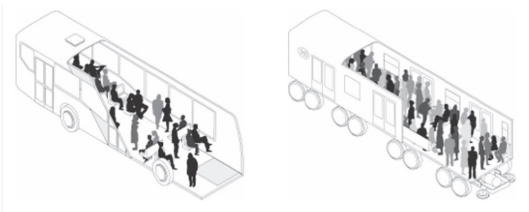
To capture passenger comfort in a manner both interpretable and sensitive to incremental load changes, we transform the continuous onboard count into a five-level ordinal index Y. This discretization distinguish between ample seating (Levels 1–2), moderate standing loads (Level 3), and high-density or overcapacity conditions (Levels 4–5). The levels where decided together with the data provider, since those levels are the same as they use in operation. A visual representation:



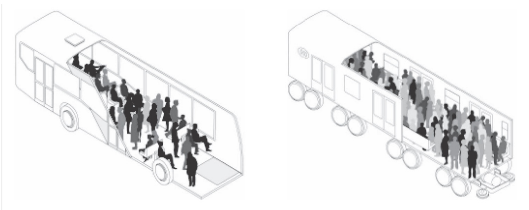
Comfort level 1: User can easily find a seat.
Occupancy $\leq$ 50% of seating capacity.



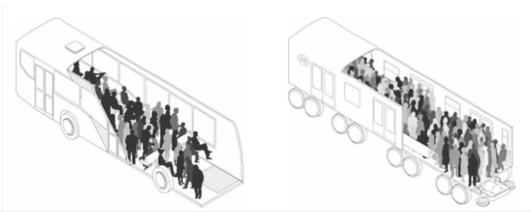
Comfort level 2: User can find a seat.
Level 1 $\leq$ Occupancy $\leq$ Seating capacity.



Comfort level 3: User cannot sit but can stand comfortably.
Level 2 $\leq$ Occupancy $\leq$ 50% of Standing capacity.



Comfort level 4: User can stand but it is crowded.
Level 3 $\leq$ Occupancy $\leq$ Designed capacity.



Comfort level 5: Overcrowded.
Occupancy $>$ Designed capacity.

Level 1 indicates conditions where fewer than half of the seats are occupied, reflecting a comfortable environment with ample seating and space. Level 2 corresponds to near-full seating occupancy, but with no standing required. Level 3 captures the onset of standing passengers up to the midpoint between seating and designed capacity, a zone where comfort begins to diminish. Level 4 denotes situations approaching full capacity, often perceived as crowded yet still within the design load. Finally, Level 5 represents overcapacity conditions, where passenger density exceeds the vehicle's nominal capacity, leading to potential discomfort and safety concerns.

3.4.2. Predictor Variables

To explain variations in comfort levels, we derive seven key predictor variables grounded in operational practice and prior literature. Each variable is computed at the stop-event level from the temporal and spatial sequence of observations in *events_analysis*. Below, we introduce each group of variables and provide an explanation of its expected behavior.

Headway Metrics

Headway regularity is a foundational determinant of passenger experience. Irregular intervals between vehicles can lead to overcrowding on delayed vehicles and underutilization of early ones.

- **Relative headway** ($\mathrm{RelHeadway}$): the percentage deviation of actual headway from the expected headway, computed as:

$$\mathrm{RelHeadway} = \frac{\mathrm{ActHeadway} - \mathrm{ExpHeadway}}{\mathrm{ExpHeadway}}$$

- **Actual headway** ($\mathrm{ActHeadway}$, seconds): the observed interval between two consecutive vehicles.
- **Bunching flag** ($\mathrm{BunchFlag} \in \{0, 1\}$): equals 1 if the actual headway is less than 90 seconds.

Relative headway quantifies the deviation between the observed headway and the scheduled interval, normalized by the scheduled value. Large relative headway values indicate vehicles that are significantly delayed compared to the expected interval, likely experiencing a buildup of waiting passengers. **Actual headway**, in contrast, captures the absolute interval (in seconds) between successive vehicles. Longer headways are generally associated with more crowding, as they imply longer passenger waiting times and greater stop-level accumulation. Finally, the **bunching flag** is a binary indicator for extremely short headways, typically indicative of vehicles operating in platoons. In this situation, the lead vehicle tends to be underloaded, while the trailing vehicle absorbs the excess demand, experiencing elevated crowding levels. While the variable marks the presence of bunching, its interpretation in modeling focuses on how that stop-event relates to uneven spacing and load concentration. According to Rezazada et al. (2024) there is no single threshold value to define bunching events, as it depends on the type of the service, time of the day, location, and service frequency. Some studies suggest using a constant threshold between 20 seconds and $^1/_4$ of the scheduled headway. For this study we chose a threshold of 90 seconds, to accommodate the headways distribution in the network.

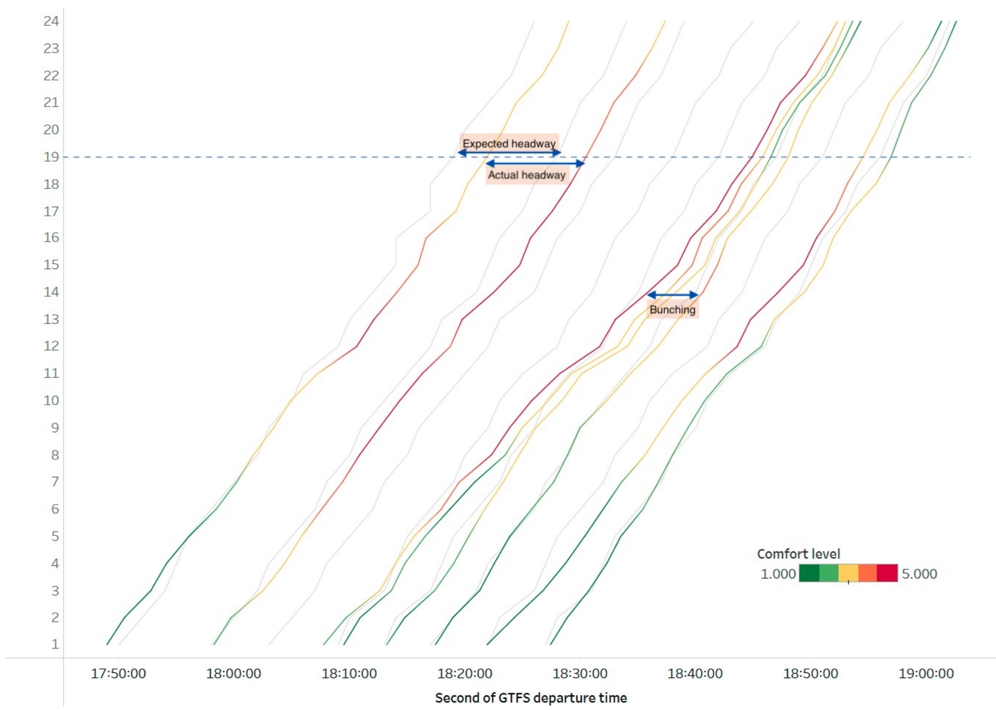


Figure 3.4.1: Headway metrics

Temporal Control

- **Peak-period flag** ($\mathrm{PeakFlag} \in \{0, 1\}$): equals 1 if the scheduled terminal time falls in peak intervals (07:00–09:00 or 16:00–19:00).

Demand in public transport systems follows strong daily cycles. To capture this, we define a **peak-period flag** that indicates whether a stop-event occurs during the morning (07:00 – 09:00) or evening (16:00 – 19:00) peaks. These intervals are associated with higher passenger volumes due to commuting activity, which often overwhelms scheduled capacity. We expect this variable to be positively associated with crowding, even after accounting for frequency and headway variation, due to background demand intensity.

Line specific metrics

- **Public transport mode**: a distinction between the three vechicle types present in the data, namely: bus, tram and trolleybus.

Vehicle configuration and capacity influence how much passenger load a vehicle can absorb before reaching crowding thresholds. In our model, **public transport mode** is included as a categorical variable to distinguish between buses, trams, and trolleybuses. Trams typically offer higher capacity and may serve more congested corridors, while trolleybuses might operate in lower-demand or segregated corridors. These differences introduce heterogeneous baseline crowding risks across modes, even under similar service conditions.

Line-Overlap Metrics

Public transport lines that share infrastructure or service arcs can produce complex interactions. On one hand, overlap increases effective frequency at shared stops; on the other hand, it increases susceptibility to demand surges and coordination failures. We include three metrics to capture this network structure.

- **Lines in arc** ($\mathrm{LinesInArc}$): number of distinct lines operating over the same arc.
- **Joint arc frequency** ($\mathrm{ArcFreq}$, trips/hour): cumulative hourly frequency of all services over the arc.
- **Upstream shared-arc ratio** ($\mathrm{SharedArcRatio}$): fraction of upstream arcs that are shared with other lines.

Lines in arc counts the number of distinct lines traversing the same road segment. A high value reflects corridor-level convergence and is expected to increase crowding risk, particularly if vehicle arrivals are poorly spaced or passenger assignment is uneven. **Arc frequency** measures the cumulative number of vehicles operating per hour over the arc. While higher arc frequency may reduce wait times and smooth demand, its interaction with headway regularity is non-linear. Under irregular conditions, high frequency may still lead to crowding due to clustering and demand peaking. Finally, the **upstream shared-arc ratio** captures the fraction of arcs prior to a given stop that are shared with other lines. A high value implies prolonged network overlap, where cumulative upstream demand can cascade into downstream segments, intensifying vehicle loading. This metric thus represents the temporal depth of exposure to network complexity.

3.4.3. Variable Summary

Variable	**Type**	**Definition / Computation**	**Expected Effect on Comfort Level**
Comfort (Y)	Ordinal (1–5)	Derived crowding index (see §3.4.1)	N/A (response variable)
Relative Headway	Continuous (unitless)	$(\mathrm{ActHeadway} - \mathrm{ExpHeadway})/\mathrm{ExpHeadway}$	Higher $\rightarrow$ More crowding due to delay-based accumulation
Actual Headway	Continuous (seconds)	Time interval between vehicles at stop level	Higher $\rightarrow$ More crowding due to longer wait times
Bunching Flag	Binary (0/1)	1 if Actual Headway $<$ 90 seconds	1 $\rightarrow$ Higher likelihood of crowding (trailing vehicles)
Peak Flag	Binary (0/1)	1 if terminal time falls in peak intervals	1 $\rightarrow$ More crowding due to increased demand
PT Mode	Categorical	Bus / Tram / Trolleybus	Trams more crowded; trolleybuses less, ceteris paribus
Lines in Arc	Discrete	Number of lines sharing the arc	Higher $\rightarrow$ Higher crowding from overlap
Arc Frequency	Continuous (trips/hour)	Sum of vehicle arrivals per hour on arc	Mixed: mitigates or worsens crowding depending on spacing
Shared Arc Ratio	Continuous (0–1)	Proportion of upstream arcs with line overlap	Higher $\rightarrow$ More crowding from upstream accumulation

Table 3.4.1: Summary of target and predictor variables and their expected influence on passenger comfort

3.5. Statistical Analysis

To examine how real-time operational factors shape in-vehicle crowding, we use a panel-data structure in which the unit of analysis is each individual stop event over the course of a service day. Specifically, we construct a cluster identifier, *panel_id*, by concatenating the stop identifier (*Stop ID*), the date of service (*Date*), and the line-direction pair (*Line-Direction*). Within each of these stop-day-line clusters, vehicles are ordered sequentially using *Trip Sequence*, which reflects their chronological position in the service schedule.

This approach produces a rich longitudinal dataset that captures the full sequence of departures at each physical stop throughout the day, allowing us to model the progression of passenger comfort as a function of service reliability and network structure.

3.5.1. Panel Structure and Model Formulation

Our panel data is indexed by:

$$(i,\, t,\, d, \ell),$$

where i refers to the physical stop, t to the trip number, d to the calendar date, and ℓ to the line-direction combination. Within each *panel_id*, multiple trips occur over time, giving us repeated observations of crowding levels under varying operational conditions.

We estimate a random-effects ordered logistic regression model of the form:

$$\log \frac{\Pr(Y_{itd\ell} \leq k)}{\Pr(Y_{itd\ell} > k)} = \alpha_k + \sum_{j=1}^{p} \beta_j X_{itd\ell,j} + u_{td\ell}, \quad k = 1, 2, 3, 4,$$

where: - $Y_{itd\ell}$ is the observed comfort level (ordinal, 1–5), - $X_{itd\ell,j}$ are the standardized service and network covariates (see Section 3.4.2), - α_k are the threshold parameters, - $u_{td\ell} \sim \mathcal{N}(0, \sigma_u^2)$ is the unobserved random intercept for each stop-day-line cluster.

This specification assumes that unobserved heterogeneity, such as persistent differences in boarding demand, infrastructure, or stop layout, is captured by the random intercept $u_{td\ell}$, which varies across clusters but not across trips within each cluster.

3.5.2. Random Effects approach

Although fixed-effects models are often used to eliminate unobserved heterogeneity that may bias regression estimates, they are not suitable in our context due to fundamental limitations of the ordered logistic model:

1. **No Conditional Likelihood Exists for Ordered Logit.** In binary logit models, the conditional likelihood method (e.g., Chamberlain estimator) can eliminate fixed effects by conditioning on the number of successes. For ordered outcomes, however, there is no analogous sufficient statistic that allows us to "condition out" the fixed effects while retaining consistent estimates of the slope coefficients.

2. **Software Limitations Reflect Fundamental Theory.** Stata's `xtologit` only supports random effects, this is not a technical omission but reflects the theoretical infeasibility of fixed-effects estimation in ordered logit models. No unbiased, consistent fixed-effects estimator is available for ordinal outcomes without relying on strong assumptions or dropping entire clusters.

3. **Practical and Theoretical Compromise.** By modeling cluster-level unobserved heterogeneity as a normally distributed random effect, we preserve the full sample and gain consistent estimates of both the slope coefficients and the variance of cluster-specific crowding tendencies. The trade-off is the assumption that these random effects are uncorrelated with the regressors.

Accordingly, all our models rely on the random-effects ordered logistic framework, striking a balance between theoretical tractability and empirical relevance in panel data with ordinal outcomes.

3.5.3. Model Diagnostics

Robustness and internal validity are essential to ensure the reliability of regression-based inference, especially in high-dimensional models where multiple predictors may be interrelated. A key concern in such settings is **multicollinearity**, which arises when two or more explanatory variables are highly correlated. In the presence of multicollinearity, the precision of estimated coefficients may be compromised: standard errors inflate, coefficient estimates become unstable, and the model may be sensitive to minor changes in the data. Although multicollinearity does not bias the estimated coefficients per se, it undermines their interpretability and statistical significance, potentially obscuring true relationships between predictors and the outcome variable.

To assess the severity of multicollinearity in our model, we calculated **Variance Inflation Factors (VIFs)** for each of the predictors included in the random-effects ordered logistic regression. The VIF for a given variable quantifies how much the variance of its estimated regression coefficient is increased due to linear dependence with the other regressors in the model. Formally, the VIF for predictor X_j is defined as:

$$\text{VIF}(X_j) = \frac{1}{1 - R_j^2}$$

where R_j^2 is the coefficient of determination obtained from regressing X_j on all other independent variables. A higher R_j^2 implies that a larger portion of X_j's variation is explained by the remaining covariates, leading to a higher VIF. As a rule of thumb, a VIF below 5 is considered unproblematic, while values above 10 indicate serious multicollinearity. Some researchers advocate a more conservative threshold of 2.5, particularly in models with large sample sizes or sensitive policy implications.

In sum, while our analysis is constrained to the random-effects ordered logistic framework by both statistical theory and software support, we implement rigorous corrections and diagnostics to ensure valid inference.

3.6. Chapter Conclusion

This chapter introduced a random-effects ordered logistic regression framework to analyze the determinants of passenger crowding in public transport. By structuring the data as a panel of stop-day-line clusters, we captured the temporal progression of service and crowding at the level of individual stops.

Due to the nature of our ordinal outcome variable and the limitations of fixed-effects estimation for such models, we adopted a random-effects specification. This approach allows us to model unobserved heterogeneity across stop-day clusters while maintaining statistical consistency and interpretability of the estimated effects, under the assumption that the random intercepts are uncorrelated with the regressors.

Our modeling strategy includes key predictors of operational reliability and network structure, as well as controls for public transport mode and peak hours. The variables are selected and defined based on theoretical expectations and practical relevance to urban public transport planning. The chapter also established a protocol for diagnostic evaluation, including checks for multicollinearity.

Chapter 4

Case Study

4.1. Case Study Description and Scope

This chapter presents a case study designed to evaluate the proposed framework in the context of real world data. Using a specific geographical and temporal scope, the case study provides insight into the operational dynamics of public transportation and highlights the potential of APC and AVL data for measuring relevant variables. Key aspects of this case study include its geographical setting, the datasets used, and the temporal focus.

4.1.1. Geographical Scope

The geographical setting for this research is in Geneva, Switzerland, encompassing the city and its surrounding areas. The focus is on the public transportation network managed by *Transports Publics Genevois* (TPG), which operates buses, trams, and trolleybuses in the area. This network spans both urban and peri-urban regions, connecting residential neighborhoods, business districts, and cross-border areas.

The network's multimodal nature makes it an ideal subject for examining interactions between different public transport modes and assessing operational performance, such as headway variability and passenger distribution and how they can relate to line overlap. These features contribute to a deeper understanding of network efficiency .

Figure 4.1.1 illustrates the Geneva public transport network, emphasizing its spatial complexity and comprehensive coverage of the region.

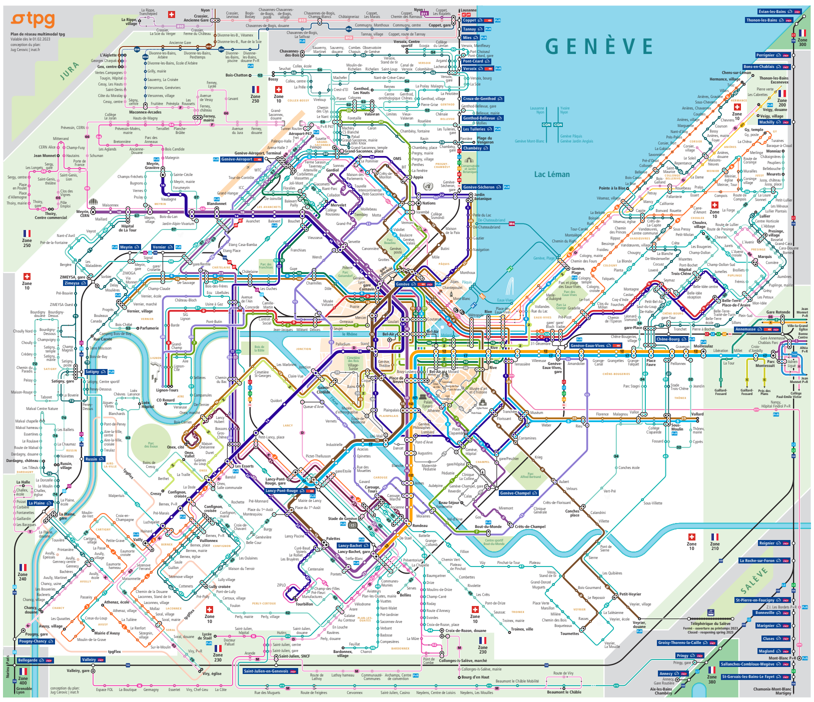


Figure 4.1.1: Geneva public transport diagram map

4.1.2. Temporal Scope

The study period spans 30 days, from November 1, 2024, to November 30, 2024. Only weekday operations are considered to focus on regular commuting patterns. Weekends are excluded to avoid anomalies caused by irregular demand. This temporal scope ensures that the analysis reflects typical weekday conditions under moderate seasonal influences. As noted by van Oort et al. (2010), headway variability significantly impacts user experience, especially for high-frequency routes where passengers arrive at stops randomly. To capture these effects, the analysis includes only routes with headways of less than 12 minutes during peak periods (Figure 4.1.2). This criterion narrows the study to high-frequency lines, ensuring a focus on routes where operational reliability and crowding effects are most significant.

Figure 4.1.2: Map of selected routes from the network

4.2. Exploratory Data Analysis (EDA)

EDA plays a critical role in uncovering the structure and behavior of key operational variables. By leveraging APC and AVL data, this study analyzes punctuality, headway variability, passenger flows, stop-level performance, and their spatial and temporal variation.

4.2.1. General Dataset Characteristics

Based on extrapolations from representative daily data, the complete sample includes approximately 1.76 million stop-level records, covering over 72,000 trips across 34 unique lines. Table 4.2.1 summarizes key indicators that describe the magnitude and scope of the data used in the analysis.

Key Performance Indicator (KPI)	Estimated Value for November 2024
Estimated total stop events	1,757,260
Estimated unique trips	72,111
Unique stops observed	245
Unique vehicles operating	348
Number of active lines	34
Percent of trips with bunching	8.67%
Percent of trips during peak	48.81%
Average cumulative frequency	13.76 vehicles/hour
Average punctuality deviation	64 seconds late
Average number of overlapping lines (lines per arc)	2.12

Table 4.2.1: Estimated Monthly KPIs from AVL/APC Data

4.2.2. Spatial Distribution of Comfort

Passenger load discomfort is not uniform across the network. Using APC-derived crowding levels, comfort levels were spatially mapped to detect areas of recurrent pressure. Figure 4.2.1 shows that central corridors and overlapping segments experience greater discomfort during peak periods, whereas peripheral stops maintain higher comfort levels during non-peak hours.

(a) Peak Hours (b) Non-Peak Hours

Figure 4.2.1: Average Comfort Level by Stop During Peak and Non-Peak Hours

4.2.3. Network Load and Cumulative Frequency

Cumulative frequency, defined as the total vehicle throughput at each stop per hour across all overlapping lines, serves as a proxy for supply density.

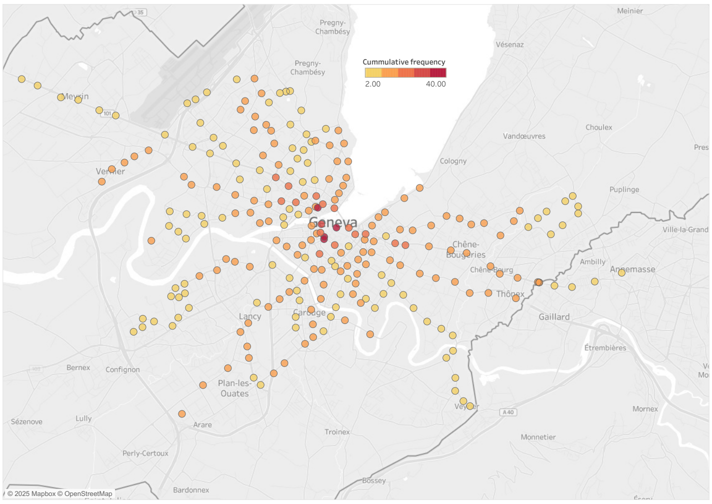


Figure 4.2.2: Average Cumulative Frequency Across the Network

4.2.4. *Headway Patterns and Bunching Events*

While most trips align with scheduled headways, a long tail is observed in the distribution, as shown in Figure 4.2.3. Additionally, Figure 4.2.4 captures the spread of actual-minus-scheduled headways.

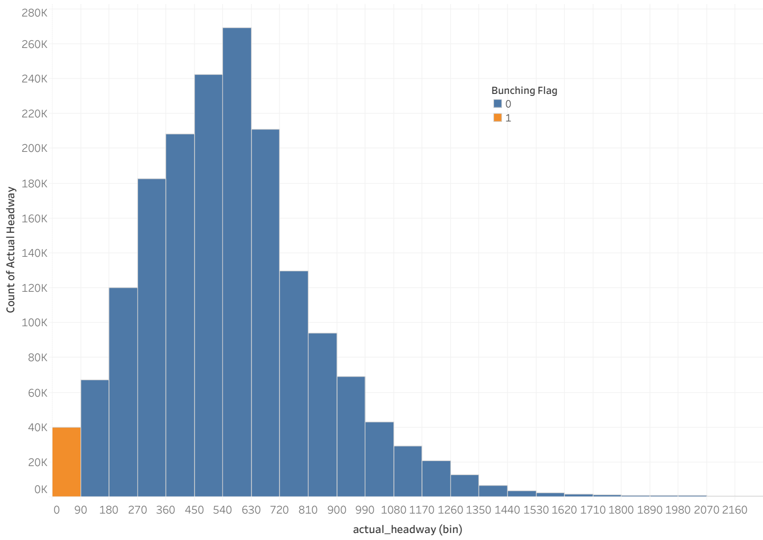


Figure 4.2.3: Distribution of Actual Headways (Minutes)

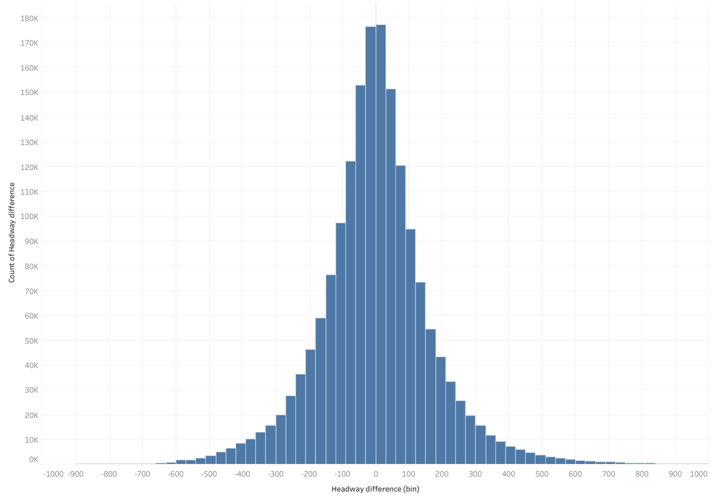
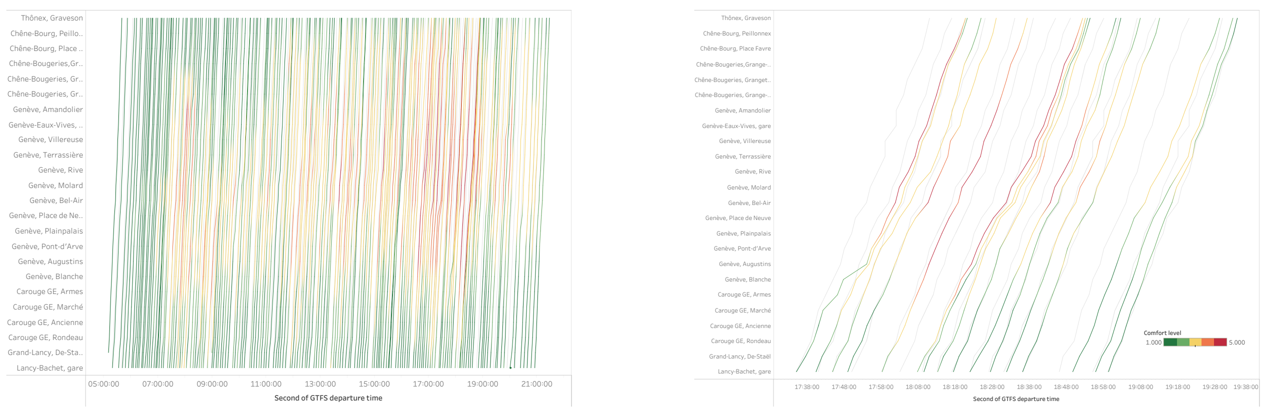


Figure 4.2.4: Difference Between Actual and Scheduled Headways

4.2.5. Temporal Dynamics and Space-Time Patterns

To observe how irregularities evolve, a representative line was selected for day-level visualization. Figure 4.2.5a shows the progression of trips throughout a normal weekday on Line 12. A zoomed-in view of a disruption is shown in Figure 4.2.5, which clearly displays a bunching episode and its ripple effect.



(a) Space-Time Plot of Line 12 on 2024-11-11

(b) Bunching Event in Line 12

Figure 4.2.5: Bunching Event Visualization Using Space-Time Plot

4.2.6. Crowding and Comfort Analysis

Crowding levels, derived from APC thresholds, are highly right-skewed. As shown in Figure 4.2.6, more than half of records are classified as Level 1 (least crowded), yet crowding above Level 3 still affects a significant portion of service, particularly in peak periods.

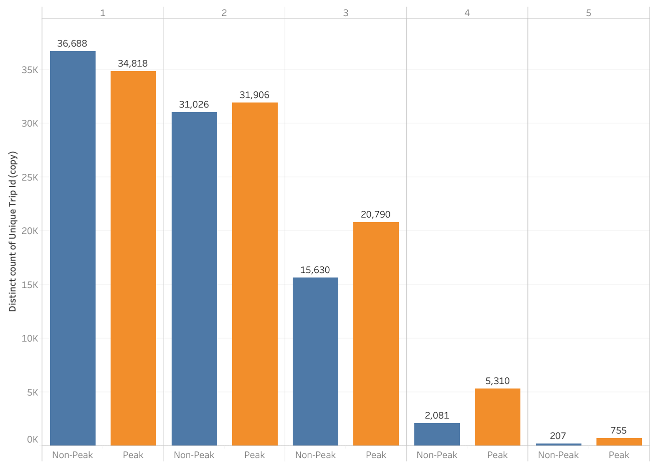


Figure 4.2.6: Passenger Comfort Level Distribution

4.2.7. *Headway Irregularity and Comfort Relationship*

Figure 4.2.7 demonstrates a monotonic relationship: relative headway increases with discomfort level. This supports the hypothesis that irregular services induce crowding by concentrating passenger arrivals and delaying the next available vehicle. The fitting formula for this relation is: $RelativeHeadway = 0.125357 \times Comfortlevel - 0.183365$ with a R^2= 0.468277

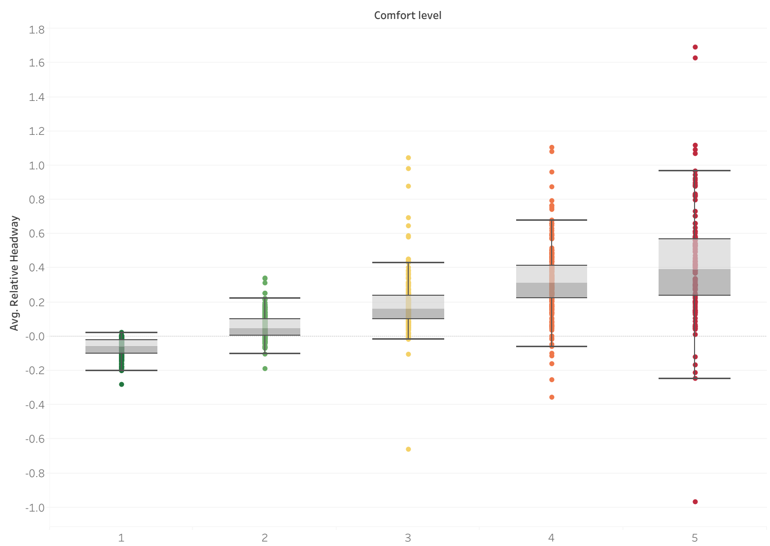


Figure 4.2.7: Relative Headway by Comfort Level

4.2.8. *Punctuality Trends*

Punctuality deviation remains mostly centered near 64 seconds late, as visualized in Figure 4.2.8. The slightly right-skewed pattern suggests structural scheduling delays, potentially due to high passenger loads and urban traffic frictions.

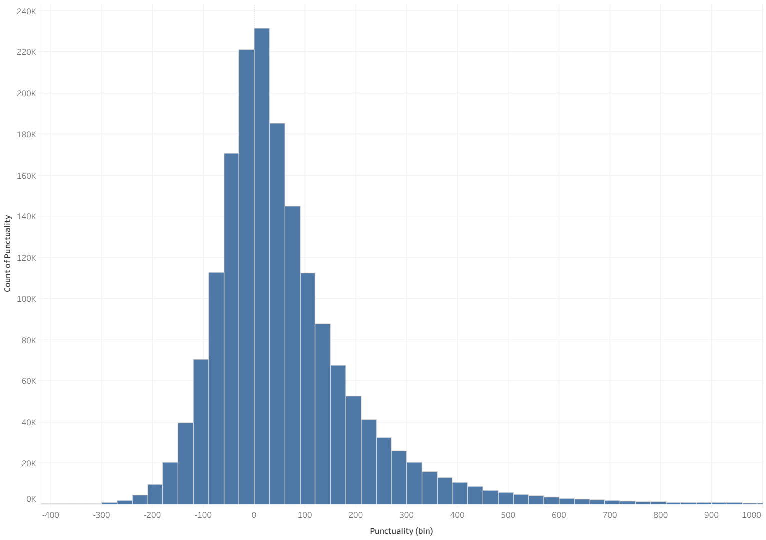


Figure 4.2.8: Distribution of Punctuality Deviations at Stops (Minutes)

4.2.9. Network Overlap and Shared Infrastructure

Network design affects operational resilience. Figure 4.2.9 illustrates how many stops per line are shared with others. Lines with higher overlap (e.g., major radial routes) also report elevated crowding and reliability issues, underscoring the importance of coordinated scheduling in shared corridors.

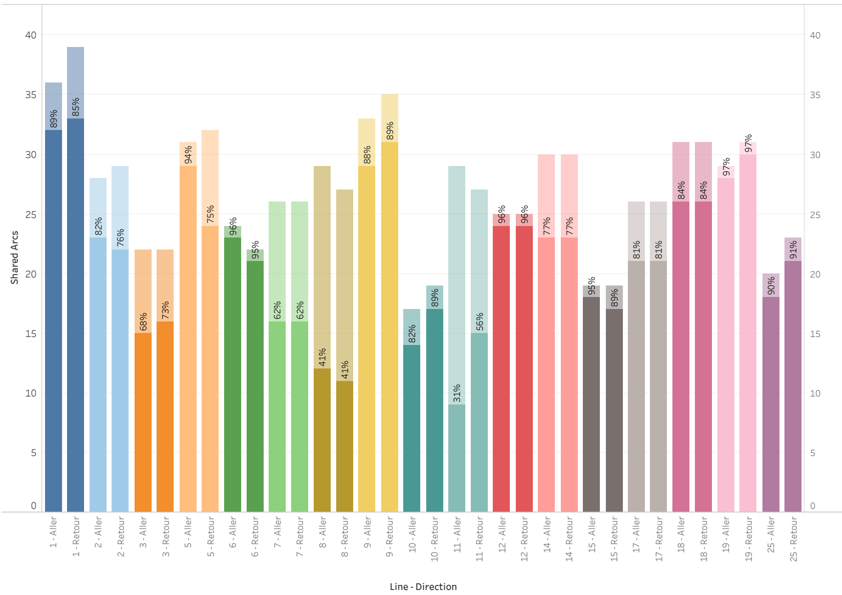


Figure 4.2.9: Stop Sharing Across Lines

4.3. Variable statistical description

Table 4.3.1 presents descriptive statistics for the comfort level index across different service conditions and vehicle modes. The table reports the mean, standard deviation, minimum, median, maximum, and sample size for all observations, during peak and non-peak periods, and separately for trolleybuses, buses, and trams.

Comfort level	Mean	Std Dev	Min	Median	Max	N	%
Overall	1.693	0.807	1	1	5	1757897	100 %
Peak	1.786	0.864	1	2	5	861088	48 %
non-Peak	1.603	0.738	1	1	5	896899	52 %
Trolleybus	1.532	0.708	1	1	5	601886	34 %
Bus	1.608	0.733	1	1	5	634607	36 %
Tram	1.981	0.918	1	2	5	521404	30 %

Table 4.3.1: Descriptive statistics for the comfort levels for different service conditions

Table 4.3.2 presents descriptive statistics for the key explanatory variables used in the ordinal regression models, disaggregated by peak and non-peak periods. For each variable, we report the mean, standard deviation, minimum, median, and maximum values, providing insight into how service characteristics differ across demand conditions.

Explanatory variables	Peak					non-Peak				
	Mean	Std Dev	Min	Median	Max	Mean	Std Dev	Min	Median	Max
Expected headway	504.2	209.1	20	480	40698	625.2	249.8	6	600	3048
Actual headway	503.2	260.2	0	484	3586	625.6	289.0	0	607	3592
Relative headway	0.008	0.481	-1	-0.01	65.13	0.01	0.590	-1	0	167.2
Lines in arc	2.113	1.112	1	2	8	2.142	1.234	1	2	8
Cumulative frequency	13.741	7.626	0.13	12.13	43.19	13.84	7.631	0.19	12.19	43.19
Upstream shared arcs	0.347	0.332	0	0.2727	1	0.333	0.329	0	0.25	1

Table 4.3.2: Descriptive statistics for predictor variables

Figure 4.3.1 presents the correlation matrix among the main explanatory variables. Overall, correlations remain moderate, suggesting that multicollinearity is not a major concern for the analysis. Actual headway and relative headway show a positive correlation (0.38), which is expected since both capture spacing between vehicles, albeit in different forms. Cumulative frequency is weakly and negatively correlated with actual headway (–0.13), indicating that higher traffic intensity is typically associated with shorter headways. Interestingly, cumulative frequency exhibits a stronger negative association with the percentage of upstream shared arcs (–0.31), reflecting that higher flow conditions might reduce route overlap consistency. Both bunching and peak flags are negatively correlated with actual headway (–0.28 and –0.22, respectively), which aligns with the idea that smaller headways often precede or occur during bunching events, particularly in peak periods. Other correlations remain close to zero, suggesting limited overlap between categorical indicators and continuous operational variables. Taken together, these results support the inclusion of all variables in the subsequent modeling framework, as they provide complementary information without excessive redundancy.

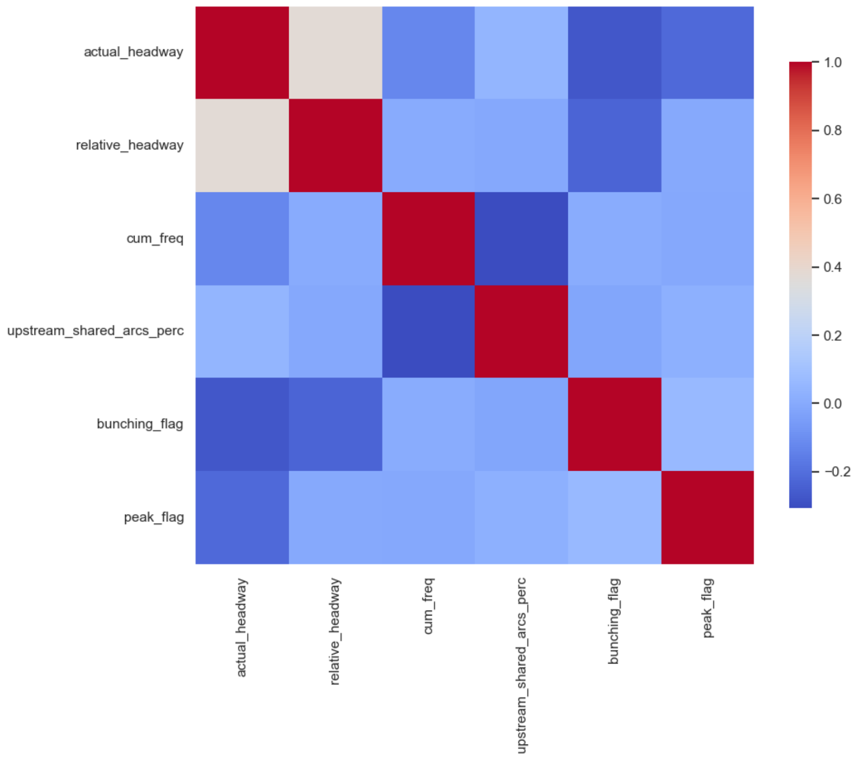


Figure 4.3.1: Correlation matrix

4.4. Chapter Conclusion

This case study confirms that APC and AVL data offer a powerful foundation for diagnosing public transport performance. From spatial comfort gradients to service irregularities, the patterns uncovered reveal complex interactions between supply, passenger accumulation, and operational timing. In particular, the findings emphasize:

- The critical role of headway variability in shaping passenger discomfort, and viceversa.
- The amplifying effect of network overlap on both crowding and punctuality.
- The presence of delays that persist and expand in the following trips.

These dynamics directly align with the theoretical framework established in Chapter **??**. The insights generated provide a solid empirical foundation for improving coordination strategies, managing corridor capacity, and enhancing reliability in multimodal public transport networks.

Chapter 5

Results

This chapter presents the empirical findings from the proposed random-effects ordered logistic regression model presented in Chapter 3, applied to over 1.75 million vehicle stop observations from the case study showed in Chapter 4. This model allows us to quantify the association between several operational and structural variables and the perceived comfort level onboard public transport vehicles, as recorded through ordinal crowding levels ranging from 1 (least crowded) to 5 (most crowded). The analysis accounts for panel-level unobserved heterogeneity by allowing each stop-day combination to have its own random intercept, thereby capturing latent features that may influence passenger load but are not explicitly measured in our data.

Our objective in this chapter is to explore how individual predictors affect the likelihood of experiencing higher crowding levels, interpret these effects substantively, evaluate model diagnostics, and discuss implications for transport planning and operations.

5.1. Model Estimation Output

Table 5.1.1 summarizes the output from the model. The estimation relies on the *xtologit* command in Stata with Gaussian-distributed random intercepts and 12-point Gauss-Hermite quadrature for numerical integration. The model is estimated on 1,757,852 observations, clustered in 18,893 unique panel units (stop-line-direction-day combinations).

Variable	**unit**	**Coef.**	**Std. Err.**	***z***	***p*-value**
Service reliability and structure					
Actual headway	[s]	0.00073	0.00001	77.24	< 0.001
Relative headway	[ratio]	0.897	0.0062	145.66	< 0.001
Cumulative frequency	[veh/h]	0.161	0.0026	61.21	< 0.001
Shared arcs upstream	[ratio]	2.989	0.0421	71.07	< 0.001
Lines in arc	[lines]	–0.090	0.0146	–6.17	< 0.001
Bunching	[binary]	–1.091	0.0154	–70.86	< 0.001
Peak period	[binary]	0.717	0.0035	204.78	< 0.001
Vehicle type (baseline: Bus)					
Tram	[category]	0.873	0.0395	22.08	< 0.001
Trolleybus	[category]	–0.740	0.0364	–20.32	< 0.001
Model fit statistics					
Log-likelihood	–1,461,786.1				
LR test vs. pooled ologit	χ^2 = 6.3e+05, $p < 0.001$				
Random intercept variance ($\sigma^2 u$)	4.061 (Std. Err. = 0.054)				
Cut	**Estimate**	**Std. Err.**	**95% CI**		
Cut 1	4.072	0.042	[3.99 ; 4.15]		
Cut 2	6.439	0.042	[6.36 ; 6.52]		
Cut 3	9.276	0.043	[9.19 ; 9.36]		
Cut 4	11.670	0.045	[11.58 ; 11.76]		

Table 5.1.1: Random-Effects Ordered Logit Estimates

The regression model provides a nuanced understanding of the operational and network-level factors that influence in-vehicle crowding, measured here through a comfort-level proxy derived from APC thresholds. The coefficients reflect the marginal effect of each predictor on the log-odds of experiencing a more crowded (i.e., less comfortable) ride. Drawing from empirical findings and theoretical insights discussed in the literature review, this section analyzes each significant predictor in depth.

5.1.1. Actual Headway

The coefficient for *Actual headway* is highly statistically significant. This variable, measured in seconds, indicates that each additional second in headway, the time elapsed since the previous vehicle, increases the probability that the vehicle will be more crowded. While the individual effect per second appears minor, when aggregated across larger headway deviations (e.g., delays of several minutes), the compounded effect becomes substantial.

This finding aligns with theoretical expectations and past literature emphasizing the link between headway irregularities and passenger accumulation. As documented by Daganzo (2009) and Tirachini et al. (2022), longer headways create temporal gaps during which passengers accumulate at stops. The longer the interval between vehicles, the more passengers are waiting for the next arrival. The arriving vehicle must then accommodate a sudden influx, which leads to higher boarding times, increased dwell, and ultimately more severe in-vehicle crowding. This crowding further delays the vehicle, initiating a negative feedback loop that degrades the reliability of the overall service.

5.1.2. Relative Headway

The *Relative headway* variable has a coefficient of 0.897, suggesting a large and statistically significant effect. Unlike absolute headway, this metric captures the deviation from the scheduled interval. In other words, it accounts for whether the observed headway is longer or shorter than expected. The positive sign indicates that the greater the deviation, especially in the direction of delay, the more likely it is that the vehicle will be crowded.

This strong effect highlights that crowding is not merely reactive to the frequency of service but also to its predictability. According to Godachevich and Tirachini (2021) and Fedujwar and Agarwal (2024), variability in service quality, particularly irregularity in headways, undermines passenger trust and leads to bunching, asymmetric boarding patterns, and inefficient load distribution. This result confirms that even in high-frequency networks, irregular headways disrupt demand distribution and increase system strain.

5.1.3. Cumulative Frequency

The coefficient for *Cumulative Frequency* (0.161) reflects the effect of aggregate vehicle throughput at a stop, essentially the number of vehicles from all lines serving that stop within an hour. This variable captures not just the intensity of service but also the likelihood of platform crowding and transfer demand, both of which correlate with higher in-vehicle densities.

While increased vehicle throughput is generally associated with improved access and reduced wait times, it can also exacerbate crowding if demand grows faster than supply. As supported by Mahmoudi et al. (2023), high-frequency services without sufficient load balancing or real-time passenger information systems tend to exhibit severe capacity strains during peaks. Moreover, cumulative frequency may also be capturing latent demand effects, areas served more intensively may do so precisely because of their elevated ridership potential, thus compounding crowding rather than alleviating it.

5.1.4. Shared Arcs Upstream

One of the most influential variables in the model is *Shared Arcs Upstream* (2.989), representing the percentage of a vehicle's upstream segment that is shared with other lines. This large and significant coefficient seems to point to a key network structure dynamic: vehicles that traverse shared corridors tend to be substantially more crowded.

As noted in the literature, overlapping routes tend to create unstable flow conditions due to inter-line interference. Diab et al. (2015) argue that overlapping increases the chances of bunching, reduces schedule adherence, and complicates holding strategies. Vehicles running through these segments not only face competition for space but also experience delay propagation from other lines. The crowding effect here reflects both greater boarding demand and greater disruption risk. Importantly, this variable's interpretation reinforces the idea that network design, not just operational management, plays a critical role in shaping crowding patterns.

5.1.5. Lines in Arc

In contrast to the previous variable, *Lines in Arc* enters the model with a negative coefficient (–0.090), suggesting a modest mitigating effect on crowding. While initially counterintuitive, this variable reflects the number of lines that traverse the current arc (not just upstream), capturing an effect of network redundancy or service options.

A plausible interpretation is that more lines in an arc may diffuse demand, giving passengers multiple alternatives and thus reducing load on any single vehicle. This supports the notion that some forms of overlapping, particularly when well-coordinated, can act as passive control mechanisms by enabling load balancing. When overlapping is coupled with real-time information, passengers may self-distribute more evenly, thereby mitigating crowding on individual vehicles. Nonetheless, this effect is likely context-dependent, and its interplay with upstream interference (captured in the previous variable) needs to be interpreted carefully.

5.1.6. Bunching Flag

The *Bunching flag* coefficient (–1.091) is large and negative, which might appear paradoxical at first glance. However, this outcome is consistent with how the flag is defined: it is coded as 1 for vehicles trailing closely behind others. In a typical bunching event, the leading vehicle absorbs the majority of waiting passengers, becoming overloaded, while the trailing vehicle arrives nearly empty.

This result is consistent with operational findings from Figliozzi et al. (2012), who describe bunching as a self-reinforcing dynamic where the leading vehicle is penalized (through increased dwell and crowding), while the trailing one gets "rewarded" by encountering fewer passengers. Importantly, this variable demonstrates that crowding is highly asymmetric within bunches, further emphasizing the critical need to prevent bunching through headway management and not just evaluate average crowding across the fleet.

5.1.7. Peak Flag

The variable *Peak flag* has a coefficient of 0.717, indicating significantly greater crowding likelihood during peak periods. This finding is consistent with intuitive and empirical expectations. Even after controlling for frequency, headway, and structural variables, peak periods remain intrinsically more crowded due to temporal surges in demand.

What this result affirms is that structural and operational interventions must be complemented by time-sensitive management strategies. As reported by Drabicki et al. (2023), peak-related crowding not only degrades passenger comfort but also increases variability in service performance, exacerbating both delay propagation and uneven load distribution. Targeted interventions such as dynamic dispatching, signal prioritization, and adaptive boarding policies are therefore particularly warranted during peak periods.

5.1.8. Vehicle Type – Tram and Trolleybus

Relative to the baseline vehicle type (Bus), *Tram* has a positive and statistically significant coefficient (0.873), while *Trolleybus* has a negative coefficient (–0.740). The tram result indicates that these vehicles, while larger in capacity, are nonetheless more crowded on average, suggesting that they serve high-demand corridors with persistent peak loads. This aligns with their role in urban networks, where trams are typically deployed on core arteries with high population and employment densities.

Conversely, the trolleybus result suggests these vehicles are used in lower-demand or more dispersed service areas. The negative coefficient reflects that they are either more frequent or encounter less demand pressure. This may also be a function of the route design or electrification priorities in quieter zones. Importantly, this variation across vehicle types suggests that crowding management should not assume uniformity across modes but be tailored to modal assignment and route function.

5.1.9. Estimated Cut Points

In ordered logit models, the estimated cut points (or thresholds) define the boundaries between adjacent categories of the dependent variable. In this study, passenger crowding levels were modeled on a five-point ordinal scale (1 = least crowded, 5 = most crowded). The four cut points represent the latent utility thresholds at which the probability of observing a higher comfort level exceeds that of the previous one.

These values indicate that the transition from lower to higher crowding categories occurs at relatively high values of the latent index, which reflects the combined linear predictor of service reliability, network structure, and contextual variables. In practical terms, this means that under average conditions most trips are classified at the lower end of the discomfort spectrum, while higher levels of crowding (crowding levels 4–5) require substantially higher contributions from predictors such as headway irregularity or high upstream overlap.

The spacing between the thresholds also provides useful insight. The relatively wide distance between Cut 1 and Cut 2 suggests that transitions from “least crowded” (level 1) to “slightly crowded” (level 2) occur more readily than shifts to higher discomfort levels. By contrast, the close spacing of the upper thresholds indicates that once vehicles approach higher crowding conditions, transitions between levels 3, 4, and 5 are more abrupt.

5.2. Model Diagnostics and Robustness

In our model, all VIFs fall well below the conservative threshold of 5, with a **mean VIF of just 1.62**, as shown in Table 5.2.1. The highest VIF, 2.87, corresponds to *Cumulative Frequency*, followed by *Lines in arc* at 2.78. These variables naturally share some correlation because areas with more overlapping lines tend to have higher service frequencies. However, the values remain safely within acceptable bounds and do not suggest harmful collinearity. Furthermore, key operational variables such as *Actual headway* (VIF = 1.45), *Relative headway* (1.22), and *Bunching flag* (1.11) show low VIFs, underscoring their independence and reliable estimation.

Importantly, these diagnostic results affirm the model's capacity to distinguish the individual contribution of each variable. The standard errors remain small and the z-statistics are high for nearly all coefficients, providing further confidence that no predictor's effect is masked or distorted by collinearity. This statistical clarity is crucial in a study of this nature, where nuanced differences in headway structure or network configuration must be interpreted distinctly.

Overall, the multicollinearity test confirms that the model estimates are robust, stable, and well-identified. The VIF analysis complements the broader model diagnostics, including goodness-of-fit statistics and likelihood ratio tests discussed earlier, and reinforces the credibility of the substantive findings on the drivers of in-vehicle crowding.

Variable	**VIF**	**1/VIF**
Cumulative frequency	2.87	0.35
Lines in arc	2.78	0.36
Actual headway	1.45	0.69
Relative headway	1.22	0.82
Shared arcs upstream	1.15	0.87
Bunching flag	1.11	0.90
Peak flag	1.07	0.93
Vehicle type (Tram)	1.52	0.66
Vehicle type (Trolleybus)	1.39	0.72
Mean VIF	1.62	

Table 5.2.1: Variance Inflation Factors for Model Predictors

5.2.1. Scenario-Based Predictions

To complement the regression coefficients, we simulated predicted probabilities of passenger comfort levels under a set of representative operating conditions. These scenarios combine realistic values of headway, overlap, demand, and vehicle type, using the estimated coefficients and cutpoints from the random-effects ordered logit model.

Table 5.2.2 reports the predicted distribution of comfort levels (1 = least crowded, 5 = most crowded) and the expected value for each scenario. The baseline case (bus, off-peak, 8-minute headway, moderate overlap) yields a very high probability of low crowding: 74.5% of events fall in comfort level 1 and the expected comfort index is 1.29. In peak conditions, crowding increases moderately (expected value 1.48), while tram operations on the same conditions show substantially higher discomfort (expected value 1.77), reflecting their deployment on high-demand corridors. In contrast, trolleybuses under the same conditions remain less crowded, with outcomes close to the baseline.

Bunching followers—vehicles arriving very shortly after a leader—show a markedly higher likelihood of low crowding (expected value 1.09), confirming that asymmetry in passenger distribution is intrinsic to bunching events. Conversely, scenarios with long headways and high overlap (13 minutes, cumulative frequency of 18 veh/h, 80% upstream overlap) display much higher crowding (expected value 2.60), with more than half of trips in levels 3–4.

Scenario	P(Y=1)	P(Y=2)	P(Y=3)	P(Y=4)	P(Y=5)	E[Level]
Baseline bus, off-peak	74.5%	22.4%	2.9%	0.2%	0.0%	1.29
Peak bus	58.8%	35.0%	5.8%	0.3%	0.0%	1.48
Peak tram	37.4%	49.1%	12.7%	0.8%	0.1%	1.77
Peak trolleybus	75.0%	22.0%	2.9%	0.2%	0.0%	1.28
Bunching follower	92.2%	7.0%	0.7%	0.0%	0.0%	1.09
Delayed + high overlap	6.4%	35.8%	50.4%	6.7%	0.7%	2.60

Table 5.2.2: Predicted comfort distributions under representative scenarios

A sensitivity analysis of actual headways confirms that expected comfort levels increase monotonically with longer gaps. For example, at 4 minutes the expected comfort level is 1.25, rising to 1.36 at 15 minutes, even when other conditions are held constant. Odds ratios derived from the model corroborate this pattern: each additional 60 seconds in headway increases the odds of higher discomfort by 4.5%, while a 0.1 increase in relative headway raises the odds by 9.4%. Overlap effects are also substantial: a 0.1 increase in the upstream shared arcs ratio raises the odds of crowding by 35%.

Finally, the random-effects structure highlights substantial unobserved heterogeneity. Simulated draws of the random intercept show that, even under identical operational conditions, expected comfort levels can range from near 1.0 to almost 1.9, reflecting stop-day specific factors such as localized demand surges or disruptions.

5.3. Chapter Conclusion

This chapter has presented a detailed examination of the estimated model's statistical properties, emphasizing both the substantive findings from the regression and the diagnostic checks necessary to ensure their validity. Using a random-effects ordered logistic regression framework, we modeled the determinants of in-vehicle crowding as measured through passenger comfort levels, incorporating key operational and structural features of the public transport network. The results provide robust and interpretable evidence linking crowding outcomes to both service reliability and network design.

Among the core insights, we observed that deviations from scheduled headways, whether measured as actual or relative, significantly increase the likelihood of crowding, reinforcing well-established theories of how irregular service degrades passenger distribution across vehicles. Similarly, indicators of network complexity, such as overlapping lines and upstream shared segments, show strong and independent effects, underscoring the operational risks embedded in corridor-based public transport design. Temporal markers like peak-hour flags and bunching indicators further reveal the compounding effects of demand surges and service compression on user experience.

Equally important, the statistical diagnostics confirm the robustness of these findings. The variance inflation factors (VIFs) remain comfortably within accepted thresholds, suggesting no evidence of problematic multicollinearity. This affirms that each explanatory variable contributes unique and interpretable information to the model, and that the parameter estimates are neither inflated nor distorted by linear dependencies among predictors.

Taken together, the results and their statistical validation provide a reliable and nuanced understanding of how public transport operations, scheduling consistency, and network geometry interact to influence crowding dynamics. These insights form a solid empirical foundation for the subsequent discussion chapter, where the broader implications for system design, passenger experience, and policy interventions are explored in depth.

Chapter 6

Discussion

This chapter synthesizes and interprets the empirical findings of the random-effects ordered logistic regression model, placing them in the broader context of public transport theory, network design, and operational performance. Building on the extensive analysis of over 1.75 million stop-level observations, the discussion aims to answer the central research question: *To what extent does headway variability explain observed in-vehicle crowding, and how does the network structure, particularly overlapping lines, moderate this relationship?*

In doing so, the chapter provides both theoretical insight and practical guidance for public transport agencies. It not only evaluates the statistical magnitude and direction of each explanatory variable but also situates these findings within real-world operational challenges. Drawing upon established literature in public transport reliability, passenger behavior, and corridor dynamics, we explore how key service attributes, such as headway regularity, route overlap, peak timing, and vehicle type, interact to shape crowding outcomes.

The discussion also revisits foundational assumptions from the literature review, including the role of passenger accumulation under stochastic arrivals, the impact of bunching on load asymmetry, and the double-edged nature of redundancy in overlapping corridors. In addition to interpreting individual coefficients, the chapter highlights systemic implications: how poor schedule adherence, insufficient coordination, and structural design flaws can create feedback loops that magnify discomfort and undermine network resilience.

6.1. Overview of Findings

The empirical analysis conducted in this study confirms that in-vehicle crowding is not a random occurrence nor solely a product of passenger demand levels, it is a structured and predictable outcome of operational performance and network design features. Using a random-effects ordered logistic regression on over 1.75 million stop-level observations, the model successfully quantified the relationships between comfort levels (as a proxy for crowding) and a comprehensive set of explanatory variables related to headway regularity, service coordination, and vehicle type.

The model's Wald ^{2} statistic of 123,215.21 ($p < 0.001$) demonstrates that the included explanatory variables jointly provide strong explanatory power. The estimated variance component for the random effects ($\hat{\sigma}_u^2 = 4.06$) indicates substantial heterogeneity across stop-day clusters, highlighting that context-specific factors beyond the included covariates continue to influence crowding dynamics.This suggests that while operational variables explain much of the variation, context-dependent dynamics, such as stop-specific boarding behavior, route geometry, or external disruptions, also shape outcomes.

These findings align with and extend prior literature. As described in Chapter 2, crowding is not merely a demand-side challenge, but a system-wide performance issue driven by the ability (or failure) of public transport networks to deliver consistent, evenly spaced service. Importantly, the analysis validates several hypothesized feedback mechanisms, such as the compounding effects of bunching, the amplifying role of overlapping corridors, and the influence of vehicle type on passenger accumulation. In doing so, the study contributes not only quantitative estimates but also a systems-level perspective that ties together operational control, infrastructure design, and passenger experience.

6.2. Headway Irregularity as a Key Driver of Crowding

Perhaps the most critical insight to emerge from the results is the central role that headway irregularity plays in generating in-vehicle crowding. Two distinct but complementary metrics were used to capture this phenomenon: *Actual headway*, representing the real-time interval between vehicles, and *Relative headway*, capturing deviation from the scheduled interval. Both variables exhibited strong, positive, and statistically significant effects on the likelihood of passengers experiencing higher crowding levels.

The coefficient on *Actual headway*, while small in absolute magnitude (0.00073), is non-negligible when contextualized. Because this variable is measured in seconds, its cumulative impact becomes evident over the types of delays commonly observed in congested networks. For instance, a five-minute increase in actual headway corresponds to an increase of over 0.2 in the log-odds of a higher crowding level. This reinforces the queuing-theoretical insight that when a vehicle is delayed, passengers continue to arrive at stops, causing the next arriving vehicle to face a disproportionately high boarding load.

Even more influential is *Relative headway*, whose coefficient of 0.897 indicates that vehicles deviating from their scheduled intervals, regardless of their average frequency, face dramatically higher odds of being overcrowded. This finding affirms earlier work by Tirachini et al. (2022) and Daganzo (2009), which emphasize that headway reliability is a stronger predictor of service quality than frequency alone. Passengers interpret deviation from schedule as a reliability failure, which not only leads to uneven load distribution but also erodes trust in the system over time.

The implications are twofold. First, service regularity should be prioritized as a performance target, particularly in high-frequency corridors where small irregularities can quickly propagate into bunching. Second, the model confirms that delays are not just problematic in temporal terms; they materially change the crowding environment inside vehicles, with real implications for comfort, safety, and passenger satisfaction.

Importantly, the strength and consistency of the headway-related coefficients validate the feedback loop described in the conceptual framework (Figure 2.5.1). A delay leads to crowding, crowding increases dwell time, and increased dwell time further disrupts headways. Once this loop is triggered, recovery becomes progressively more difficult without active control strategies. This underscores the operational necessity of dynamic interventions, such as real-time holding, skip-stopping, or even dynamic re-dispatching, to mitigate the compounding effects of early headway deviations.

In summary, this study provides rigorous empirical evidence that confirms and quantifies what many public transport planners have long understood intuitively: headway regularity is not a peripheral concern, it is a primary determinant of service quality. As such, it should be central to both strategic planning and day-to-day operational control.

6.3. Bunching and Peak Effects

The dynamics of bunching, long recognized in both theoretical and empirical public transport literature, emerged clearly in this study. The negative coefficient associated with the *bunching flag* variable confirms that vehicles participating in a bunch, specifically the trailing vehicles, are significantly less crowded than the leading one. This reflects the basic operational reality: vehicles that run closely behind another typically encounter stops with fewer waiting passengers, as most riders have already boarded the lead vehicle. Thus, the front vehicle is "underloaded," while the trailing vehicle becomes increasingly crowded.

The implications of this pattern are twofold. First, underloaded trailing vehicles represent a direct efficiency loss: energy is consumed and operator time expended to transport partially full vehicles, while leading vehicles bear the burden of crowding. Second, from a passenger perspective, this leads to inconsistent comfort levels and increases the randomness of service quality. Riders encountering bunched vehicles might face either an empty or overcrowded vehicle, depending on their stop position and timing. Overall the global result is that the comfort level of more passengers is affected.

Importantly, this phenomenon underscores the limitations of frequency-based planning in high-frequency corridors. While increased frequency can reduce average wait times, without effective headway management, the system remains vulnerable to bunching-driven service degradation. Mitigation strategies such as dynamic holding, real-time spacing control, or even stop-skipping during bunches should be considered to restore balance and improve load distribution.

Turning to the *peak flag*, the strong positive effect of peak hours on crowding is unsurprising but vital. Morning and evening peaks coincide with concentrated travel demand, commuters heading to work or returning home, which overloads even well-designed schedules. Even after controlling for service frequency, bunching, and vehicle type, peak periods independently predict higher crowding levels. This indicates that demand surges outpace supply in temporal windows, reinforcing the need for adaptive operational strategies.

While longer-term infrastructure investments (e.g., public transport signal priority, dedicated lanes) remain important, the findings suggest that soft interventions, such as temporal dispatch smoothing, short-turning, or capacity reallocations, may offer near-term relief. Additionally, crowding mitigation during peaks is not solely a question of throughput; it's about temporal fairness: ensuring that riders traveling during rush hours do not disproportionately suffer degraded conditions.

6.4. Line Overlap and Corridor Effects

Transit network structure plays a crucial and sometimes underappreciated role in shaping crowding dynamics. This study included two variables, *Shared upstream arcs* and *lines in arc*, to capture different aspects of line overlap and corridor complexity. These variables provide insight into how shared routing geometry and service interdependencies affect crowding outcomes.

The percentage of shared upstream arcs demonstrates a strong positive relationship with crowding, suggesting that as multiple lines converge before a given stop, they effectively funnel more passengers into the same downstream vehicles. This "funneling effect" reflects both accumulated demand and the synchronization challenge that overlapping routes impose. When lines share segments, delays on one can propagate to others, compounding headway variability and increasing the risk of uneven passenger loading. As observed by Drabicki et al. (2023), overlapping services, while theoretically beneficial, often underperform unless actively managed.

Conversely, the negative coefficient for *lines in arc* introduces an interesting nuance. It suggests that more lines operating on a shared arc may distribute passengers more evenly, potentially due to higher frequencies and diversified boarding options. In essence, while upstream convergence builds up load, having multiple downstream options may mitigate the final distribution of passengers across services. This indicates that the spatial structure of overlap matters: convergence before a stop (upstream) has crowding risks, but co-located services at the stop itself may enable better demand absorption, particularly when headways are managed or when stop-level information is available to passengers.

The broader planning implication is that line overlap is not inherently good or bad; it is context-dependent. When designed thoughtfully and paired with appropriate coordination strategies (e.g., offset dispatching, integrated headway planning), overlapping routes can deliver both redundancy and resilience. However, absent control, they risk amplifying the very irregularities they were meant to mitigate. Planners must therefore distinguish between passive redundancy (lines simply crossing) and active coordination (lines operating in synchronized harmony).

6.5. Role of Vehicle Type

Finally, the effect of vehicle type on crowding highlights how rolling stock selection and mode deployment strategies intersect with operational outcomes. With buses as the reference group, both trams and trolleybuses showed significant differences in associated crowding levels, but in opposite directions.

The positive association between tram operations and increased crowding levels (0.873 in log-odds) likely reflects both demand and supply-side factors. Trams are often deployed on high-ridership corridors where they act as backbone services. These corridors naturally attract larger passenger volumes due to central locations, dense land use, and modal connectivity. Additionally, trams have higher nominal capacities, which may result in operations being optimized closer to saturation. While this makes them efficient in terms of cost per passenger, it also implies that crowding levels can increase even if operational targets are met. These findings align with prior literature showing that comfort, not just capacity utilization, is a key determinant of service quality (Tirachini et al., 2016).

By contrast, trolleybuses appear less crowded, as indicated by the negative coefficient. This may stem from their deployment pattern: in many systems, trolleybuses serve medium-density corridors where electrification is feasible but passenger volumes do not warrant higher-capacity vehicles. Alternatively, they may run at higher frequencies or serve less complex routes with fewer overlaps, thereby enjoying greater headway regularity. These vehicles tend to be more comfortable or spacious due to quieter engines and smoother acceleration, factors not captured directly in the model.

From a policy standpoint, the results suggest that mode choice should be linked not just to demand forecasts, but also to projected crowding tolerance and desired service quality levels. Deploying trams or large-capacity vehicles on high-demand corridors is efficient, but without supplementary crowding mitigation (e.g., larger stop platforms, boarding control, or skip-stop operations), it risks compromising user comfort. Meanwhile, trolleybus operations may represent an opportunity for targeted investments in underserved areas, combining low-emission technology with lower baseline crowding.

6.6. Implications for Network Design and Operations

The empirical findings of this study carry direct and actionable implications for the design and operation of public transport networks. Perhaps the most salient message is that crowding is not simply a by-product of demand intensity, it is a systemic outcome shaped by the interaction of operational variability, service topology, and scheduling policy. As such, improving comfort levels requires a shift from capacity-focused planning to a more integrated approach centered on predictability and spatial coordination.

First and foremost, the central role of headway irregularity in driving crowding highlights the need for robust headway management strategies. Traditional frequency-based planning, while sufficient in low-demand contexts, fails to address the cascading effects of variability under high-load conditions. This study confirms that even modest deviations from scheduled headways produce disproportionate impacts on passenger distribution, particularly in overlapping corridors. Agencies should therefore invest in dynamic control policies, such as real-time headway spacing algorithms, holding strategies, and schedule adherence monitoring. Such interventions are especially valuable in mixed-traffic environments where uncontrollable external factors (e.g., traffic congestion, signal delays) disrupt regularity.

Second, the dual role of line overlapping underscores the importance of distinguishing between structural redundancy and operational interdependence. Overlapping routes, when uncoordinated, introduce timing conflicts that amplify bunching and passenger imbalance. However, when coordinated, they offer substantial benefits in terms of service flexibility and frequency. One concrete implication is that overlapping services should not be left to operate independently on shared corridors. Instead, they should be scheduled as a joint system, with offset headways, harmonized stop patterns, and shared dispatching logic. This not only prevents crowding but also ensures that the benefits of redundancy translate into usable capacity.

Network design should also consider the spatial sequence of overlaps. The finding that upstream shared segments are strongly associated with crowding suggests that where lines merge has as much impact as how many lines merge. If overlaps occur too far upstream of major boarding stops, crowding can build prematurely, resulting in capacity exhaustion before key transfer points. In contrast, strategically placing overlaps downstream or near central nodes may allow for better load distribution. This insight supports the growing advocacy for demand-sensitive route restructuring, optimizing not just line length or stop spacing, but also the interaction between lines at key arcs.

The observed differences in crowding across vehicle types suggest that mode deployment should account for more than just corridor demand. For instance, trams may be better suited for corridors where high volumes are expected but must be paired with infrastructure that supports fast boarding, alighting, and dwell time management. Trolleybuses, on the other hand, could be prioritized for routes where consistent comfort is desired, perhaps due to demographic considerations (e.g., elderly passengers) or service branding.

Finally, the significant random effects identified at the stop-day level point to unobserved heterogeneity in crowding determinants, such as weather, special events, or temporal anomalies. This suggests that static service planning alone is insufficient. Agencies should develop feedback systems that incorporate day-to-day operational data (e.g., from AVL/APC systems) into continuous planning loops. In particular, machine learning or hybrid prediction models could anticipate crowding patterns based on temporal-spatial features, allowing for dynamic resource reallocation or passenger information updates in real time.

In sum, the results argue for a holistic redesign of public transport planning paradigms: one that merges spatial network design with operational responsiveness. Such integration is essential not just for efficiency, but for ensuring a reliable, equitable, and passenger-friendly urban mobility system.

6.7. Chapter Conclusion

The findings presented in this chapter reinforce a central insight of contemporary public transport planning: that operational reliability and spatial coordination are as critical to passenger comfort as raw capacity or frequency. Through the lens of a large-scale, random-effects model, we have demonstrated that irregular headways, service bunching, and uncoordinated line overlaps are not merely incidental inefficiencies, they are systematic drivers of in-vehicle crowding, capable of eroding service quality even when overall vehicle throughput appears sufficient.

Headway variability emerged as the most potent predictor of crowding levels, both in its absolute and relative form. This confirms longstanding theoretical models which posit that unpredictable intervals between vehicles trigger uneven passenger accumulation, thereby producing overloaded vehicles even under moderate demand. More importantly, the results underscore the amplifying effect of network design: overlapping lines, especially those converging upstream of key boarding stops, compound the effect of variability by concentrating demand in ways that cannot be resolved through frequency increases alone.

The chapter has also drawn attention to subtler dynamics such as the phenomenon of bunching, where leading vehicles are disproportionately affected by overload, and the asymmetric crowding patterns observed across vehicle types. These nuances matter. They suggest that blanket policies (e.g., uniform headway targets or fleet assignments) may miss opportunities for localized optimization based on stop-level or corridor-level dynamics.

From a strategic perspective, the implications are clear. Agencies must move toward network designs that are not just redundant, but resilient, capable of absorbing fluctuations without collapsing into disorder. This requires integrating real-time operational control with long-term corridor planning, especially in overlapping segments. Vehicle types should be deployed with sensitivity to both capacity and boarding behavior. And, perhaps most importantly, headway regularity must be elevated from a performance indicator to a core design principle.

In conclusion, crowding is not simply a function of how many passengers are onboard, but of how predictably and coherently services are delivered across space and time. Addressing it will require more than infrastructure, it demands coordination, monitoring, and adaptive planning rooted in an empirical understanding of how variability propagates through the system. The evidence presented here provides a strong foundation for that shift.

Chapter 7

Conclusions

This chapter synthesizes the insights generated throughout this research, linking them back to the research questions and objectives defined in Chapter 1. Drawing upon theoretical insights from the literature and empirical evidence from the data-driven model, the study provides a comprehensive examination of how headway variability and line overlapping interact to influence in-vehicle crowding in urban public transport systems. The chapter is organized as follows: first, the main findings are recapped in relation to the central research question and its sub-questions; then, the scientific and practical contributions are summarized; finally, limitations and directions for future research are discussed.

The primary objective of this thesis was to evaluate the relationship between headway variability, in-vehicle crowding, and the effects of overlapping public transport lines. In doing so, the research aimed to answer the following central question:

> ***How much of the variability in in-vehicle crowding levels can be explained by headway variability in bus or tram lines, and what is the impact of line overlapping on this relationship?***

Through the use of a large-scale dataset derived from Automatic Passenger Count (APC), Automatic Vehicle Location (AVL), and GTFS data, and the estimation of a random-effects ordered logistic regression model, this research has been able to quantify the influence of headway-related variables and network configuration features on reported passenger comfort levels, used here as a proxy for in-vehicle crowding.

7.1. Main Findings and Research Questions Answered

RQ1: What is the theoretical relationship between in-vehicle crowding, headway variability, and line overlapping in a public transport system?

Drawing from the literature reviewed in Chapter 2, a conceptual model was constructed to understand the cyclical feedback loops among headway irregularity, overlapping segments, and crowding. Headway variability induces uneven passenger accumulation, resulting in differential boarding loads across vehicles. This leads to extended dwell times and further disrupts headway consistency. Line overlapping, meanwhile, introduces inter-line dependencies, which magnify the impact of disruptions by transmitting delays between routes. Together, these factors operate in reinforcing cycles, exacerbating both crowding and operational instability.

RQ2: How can AVL and APC data be used to accurately measure and analyze in-vehicle crowding and headway variability?

This study successfully demonstrated that APC and AVL data can be harnessed to derive granular, high-frequency indicators of both crowding and service irregularity. The crowding level variable, obtained from APC thresholds, served as a reliable ordinal proxy for crowding. Headway variability was operationalized through both absolute and relative headway metrics. APC data revealed crowding distributions, while AVL time-stamps enabled the reconstruction of headway patterns at fine spatial and temporal resolutions. This integration of data streams proved crucial for diagnosing systemic inefficiencies.

RQ3: How can existing empirical models of crowding be enhanced by incorporating both headway variability and line overlapping?

The random-effects ordered logistic model allowed for a nuanced exploration of how operational and network variables influence crowding levels across more than 1.7 million stop events. Headway metrics were among the most powerful predictors in the model: actual headway had a consistently positive association with discomfort levels, while relative headway, capturing deviation from schedule, was even more impactful. Overlapping-specific metrics, such as the percentage of shared upstream arcs and the number of lines in the corridor, provided additional explanatory power, suggesting that crowding is not merely a function of frequency, but of how services are structured and interlinked.

7.2. Theoretical and Empirical Contributions

This thesis advances both theoretical and empirical understanding of crowding dynamics in high-frequency, surface-based public transportation systems. By bringing together concepts that are often treated independently, namely headway variability, line overlapping, and in-vehicle crowding, this work establishes a unified analytical framework capable of capturing their interdependent effects on passenger experience.

7.2.1. Theoretical Contributions

From a theoretical perspective, the study synthesizes several threads in transportation research by embedding service irregularity and network structure into a single explanatory model. Prior literature has typically explored headway regularity and overlapping routes in separate domains, with crowding often treated as a downstream outcome rather than a feedback mechanism. This thesis shows that these elements cannot be meaningfully disentangled: headway variability exacerbates crowding, crowding increases dwell times, and overlapping routes multiply the opportunities for these processes to interact in complex, path-dependent ways.

Moreover, the empirical confirmation of these interactions strengthens long-standing theoretical propositions from queueing theory and operational control studies. The findings validate the hypothesis that overlapping lines, although beneficial in terms of frequency and network redundancy, introduce coordination burdens that degrade reliability and contribute to uneven passenger loading, particularly when upstream services are not designed jointly. In doing so, the thesis not only reinforces theoretical expectations but extends them by quantifying the effects across a large and diverse set of service instances.

7.2.2. Empirical Contributions

On the empirical front, the study makes several meaningful contributions. First, it demonstrates, using a dataset of over 1.75 million stop-level observations, that headway irregularity is a primary and consistent driver of in-vehicle crowding. This finding holds even after controlling for route structure, vehicle type, temporal variation, and stop-level heterogeneity. Relative headway deviations, in particular, emerge as a potent predictor, underscoring the central role of temporal coordination in shaping passenger experiences.

Second, the analysis reveals how overlapping routes do not uniformly alleviate crowding through increased frequency; rather, they introduce interdependencies that, when unmanaged, generate concentrated loading patterns and service inconsistencies. While shared corridors may disperse demand under ideal conditions, they also serve as vectors for delay propagation and bunching, especially in high-volume settings where minor irregularities are amplified downstream.

Finally, the application of a random-effects ordered logistic regression model represents a methodologically appropriate and novel approach to modeling ordinal passenger comfort data in a repeated-observations framework. By modeling random intercepts at the stop-day level, the model captures the latent, context-specific factors, such as weather, special events, or localized disruptions, that influence comfort but are difficult to observe directly. This approach balances statistical rigor with operational relevance and opens the door for more nuanced, data-rich evaluations of public transport service quality.

7.3. Policy and Operational Implications

The findings of this thesis carry direct implications for public transportation planning, network design, and service control. Operationally, the results reinforce the critical importance of maintaining consistent headways as a means of crowding mitigation. Variability in inter-vehicle spacing not only reduces reliability but also distorts the distribution of passengers across vehicles, leading to inefficiencies and discomfort that are both perceptible to riders and costly to operators.

Transit agencies should therefore prioritize headway-based control strategies, such as holding at key stops, real-time dispatch coordination, or adaptive signal priority, as core tools for improving comfort and performance. These measures are especially vital in corridors with overlapping lines, where the synchronization of services becomes both more challenging and more impactful. The modeling results make clear that overlap must be actively managed; otherwise, it risks becoming a source of network fragility rather than flexibility.

From a network design standpoint, the study highlights the trade-offs inherent in overlapping service design. While overlapping lines can improve access and increase effective frequency at shared stops, they also introduce a heightened risk of systemic delays when service irregularities propagate across routes. This suggests that overlapping segments should be carefully identified and supported with operational redundancies, infrastructure (e.g., dedicated lanes or queue jumps), and digital tools for real-time monitoring and passenger information.

Furthermore, the role of vehicle type in crowding dynamics suggests that fleet composition and deployment should be sensitive not just to ridership forecasts but also to route geometry and variability profiles. Trams, while typically larger and better suited for high-demand corridors, tend to exhibit higher reported crowding levels, perhaps due to longer loading times or greater variance in stop density. Trolleybuses, by contrast, appear better suited for corridors with stable or moderate demand, especially where maneuverability or precision scheduling are critical.

In short, the thesis points to a paradigm in which comfort outcomes are less a function of raw capacity and more a product of finely tuned operations, coordinated scheduling, and context-aware network architecture.

7.4. Limitations

Despite the breadth and granularity of the dataset used, several limitations constrain the generalizability and interpretability of this work.

First, the dependent variable, passenger comfort level, is inferred from automated passenger count thresholds rather than direct survey data. While empirically grounded and consistently applied, this measure may not fully reflect subjective perceptions of crowding, which are known to vary based on duration, cultural expectations, and psychological thresholds.

Second, the assumption of proportional odds across ordinal thresholds, inherent to the ordered logistic framework, may not always hold in practice. That is, the relationship between predictors and comfort may not be uniform across all thresholds, moving from level 2 to 3 may not imply the same behavioral or experiential jump as from 4 to 5. Future research might consider generalized ordered models or partial proportional odds specifications to relax this assumption.

Third, the random-effects specification captures heterogeneity at the stop-day level but does not account for higher-order clustering (e.g., at the route or operator level) that could further influence crowding dynamics. Multilevel or hierarchical models might provide an even richer understanding of how systemic, spatial, and organizational factors interact to produce the observed outcomes.

Lastly, while the findings are statistically robust, they remain observational in nature. Causal claims, particularly those informing intervention efficacy, would be strengthened by natural experiments, instrumental variable designs, or simulation-based validations.

7.5. Future Research Directions

This thesis opens several promising pathways for future work. A natural extension lies in dynamic modeling of headways and crowding over time. Rather than treating each stop-event as independent, time-series could be employed to track the temporal evolution of irregularity and its lagged effects on passenger loads. Time-series models would also be better suited to evaluating control strategies that unfold over successive trips or days.

Another fruitful direction involves simulating operational interventions. By embedding the empirical relationships identified here into a simulation environment, one could evaluate the real-time impacts of holding, priority signaling, or dynamic re-routing under different demand and disruption scenarios. This would provide agencies with actionable, context-specific guidelines for control policy design.

Finally, the methods and frameworks developed in this thesis are ripe for application in comparative studies across cities. Urban areas with different levels of network complexity, modal integration, or institutional capacity may exhibit distinct patterns in the crowding–headway–overlap nexus. A system-wide analysis of this sort could yield valuable typologies of public transport system resilience and reveal which structural features are most critical to equitable and efficient public transport.

7.6. Final Remarks

Crowding in public transportation is not merely a manifestation of excess demand; it is a signal of systemic fragility in the face of temporal irregularity and spatial interdependence. This thesis has shown that even in high-frequency networks, comfort outcomes are highly sensitive to deviations in scheduled operations and to the structural design of shared corridors. It has also shown that these effects are not uniformly negative or positive, rather, they depend on the capacity of the system to coordinate, adapt, and inform.

By combining theoretical reasoning with large-scale empirical analysis, this research has clarified how and why crowding emerges, who it affects, and what can be done to mitigate it. The challenge now is not only to monitor and model these dynamics, but to institutionalize them in the way public transport systems are designed, managed, and governed.

Reliable service and dignified travel are not luxuries, they are the baseline for a sustainable and inclusive urban future. This work aims to contribute a step in that direction.

Bibliography

References

Arriagada, J., Gschwender, A., Munizaga, M. A., & Trépanier, M. (2019, 7). Modeling bus bunching using massive location and fare collection data. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *23*(4), 332–344. doi: 10.1080/15472450.2018.1494596

Barabino, B., Di Francesco, M., & Mozzoni, S. (2017, 7). Time Reliability Measures in bus Transport Services from the Accurate use of Automatic Vehicle Location raw Data. *Quality and Reliability Engineering International*, *33*(5), 969–978. doi: 10.1002/qre.2073

Barabino, B., Raccagni, L., & Ventura, R. (2025, 4). Accuracy of Automatic Passenger Counting in Open Mass Transit Systems: Insights from Italy. *The Open Transportation Journal*, *19*(1). Retrieved from https://opentransportationjournal.com/VOLUME/19/ELOCATOR/e26671212383074/ doi: 10.2174/0126671212383074250407062430

Batarce, M., Muñoz, J. C., & Ortúzar, J. d. D. (2016, 9). Valuing crowding in public transport: Implications for cost-benefit analysis. *Transportation Research Part A: Policy and Practice*, *91*, 358–378. doi: 10.1016/j.tra.2016.06.025

Cavallero, A., Caravello, A., Colombo, L., Dalla Chiara, B., Urso, P., & Zanini, M. (2023, 11). Automatic passenger counting on buses for local public transport: evaluation of the reliability of a system based on pressure sensors. *Ingegneria Ferroviaria*, 773–793.

Chen, S., & Liu, D. (2011). *Assessing the Influence of Public Transit Headway Irregularity on Passenger's Distribution* (Tech. Rep.).

Daganzo, C. F. (2009). A headway-based approach to eliminate bus bunching: Systematic analysis and comparisons. *Transportation Research Part B: Methodological*, *43*(10), 913–921. doi: 10.1016/j.trb.2009.04.002

Diab, E., Bertini, R., & El-Geneidy, A. (2015). *Bus transit service reliability: Understanding the impacts of overlapping bus service on headway delays and determinants of bus bunching* (Tech. Rep.).

Ding, Y., & Chien, S. I. (2001). *Improving Transit Service Quality and Headway Regularity with Real-Time Control* (Tech. Rep.).

Drabicki, A., Cats, O., & Kucharski, R. (2021, 6). The potential of real-time crowding information in reducing bus bunching under different network saturation levels. In *2021 7th international conference on models and technologies for intelligent transportation systems, mt-its 2021.* Institute of Electrical and Electronics Engineers Inc. doi: 10.1109/MT-ITS49943.2021.9529310

Drabicki, A., Kucharski, R., & Cats, O. (2023, 6). Mitigating bus bunching with real-time crowding information. *Transportation*, *50*(3), 1003–1030. doi: 10.1007/s11116-022-10270-3

Fedujwar, R., & Agarwal, A. (2024). A systematic review on crowding valuation in public transport. *Public Transport*. doi: 10.1007/s12469-024-00363-w

Feng, W., & Figliozzi, M. (2011). *Empirical findings of Bus Bunching Distributions and Attributes Using Archived AVL/APC Bus Data* (Tech. Rep.).

Figliozzi, M., Feng, W.-c., Laferriere, G., & Feng, W. (2012, 7). *A Study of Headway Maintenance for Bus Routes: Causes and Effects of "Bus Bunching" in Extensive and Congested Service Areas* (Tech. Rep.). Portland State University. Retrieved from http://archives.pdx.edu/ds/psu/11482 doi: 10.15760/trec.107

Godachevich, J., & Tirachini, A. (2021, 12). Does the measured performance of bus operators depend on the index chosen to assess reliability in contracts? An analysis of bus headway variability. *Research in Transportation Economics*, *90*. doi: 10.1016/j.retrec.2020.101000

GTFS.org. (2024). *What is gtfs?* Retrieved from https://gtfs.org/getting-started/what-is-GTFS/ (Accessed: 2025-06-09)

Hole, A. R., Dickerson, A., & Munford, L. (2011, Sep). *A review of estimators for the fixed-effects ordered logit model* (United Kingdom Stata Users' Group Meetings 2011 No. 05). Stata Users Group. Retrieved from https://ideas.repec.org/p/boc/usug11/05.html doi: None

Iliopoulou, C. A., Milioti, C. P., Vlahogianni, E. I., & Kepaptsoglou, K. L. (2020, 7). Identifying spatio-temporal patterns of bus bunching in urban networks. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *24*(4), 365–382. doi: 10.1080/15472450.2020.1722949

Lin, J., & Ruan, M. (2009). Probability-based bus headway regularity measure. *IET Intelligent Transport Systems*, *3*(4), 400–408. doi: 10.1049/iet-its.2008.0088

Mahmoudi, R., Saidi, S., & Wirasinghe, S. C. (2023). Optimal vehicle capacity and dispatching policy considering crowding in public bus transit services. *Transportmetrica A: Transport Science*. doi: 10.1080/23249935.2023.2258996

Martínez-Estupiñan, Y., Delgado, F., Muñoz, J. C., & Watkins, K. E. (2023, 8). Improving the performance of headway control tools by using individual driving speed data. *Transportation Research Part A: Policy and Practice*, *174*. doi: 10.1016/j.tra.2023.103761

Muñoz, J. C., Soza-Parra, J., & Raveau, S. (2020, 1). A comprehensive perspective of unreliable public transport services' costs. *Transportmetrica A: Transport Science*, *16*(3), 734–748. doi: 10.1080/23249935.2020.1720861

Rezazada, M., Nassir, N., Tanin, E., & Ceder, A. (2024). Bus bunching: a comprehensive review from demand, supply, and decision-making perspectives. *Transport Reviews*, *44*(4), 766–790. doi: 10.1080/01441647.2024.2313969

Soza-Parra, J., Muñoz, J. C., & Raveau, S. (2021). Factors that affect the evolution of headway variability along an urban bus service. *Transportmetrica B*, *9*(1), 479–490. doi: 10.1080/21680566.2021.1906350

Soza-Parra, J., Raveau, S., & Muñoz, J. C. (2022, 4). Public transport reliability across preferences, modes, and space. *Transportation*, *49*(2), 621–640. doi: 10.1007/s11116-021-10188-2

Soza-Parra, J., Raveau, S., Muñoz, J. C., & Cats, O. (2019, 8). The underlying effect of public transport reliability on users' satisfaction. *Transportation Research Part A: Policy and Practice*, *126*, 83–93. doi: 10.1016/j.tra.2019.06.004

Strathman, J. G., Kimpel, T. J., & Trimet, S. C. (n.d.). *Headway Deviation Effects on Bus Passenger Loads: Headway Deviation Effects on Bus Passenger Loads: Analysis of Tri-Met's Archived AVL-APC Data Analysis of Tri-Met's Archived AVL-APC Data* (Tech. Rep.). Retrieved from `https://pdxscholar.library.pdx.edu/cus_pubs/62`

Tirachini, A., Godachevich, J., Cats, O., Muñoz, J. C., & Soza-Parra, J. (2022). Headway variability in public transport: a review of metrics, determinants, effects for quality of service and control strategies. *Transport Reviews*, *42*(3), 337–361. doi: 10.1080/01441647.2021.1977415

Tirachini, A., Hensher, D. A., & Rose, J. M. (2013). Crowding in public transport systems: Effects on users, operation and implications for the estimation of demand. *Transportation Research Part A: Policy and Practice*, *53*, 36–52. doi: 10.1016/j.tra.2013.06.005

Tirachini, A., Sun, L., Erath, A., & Chakirov, A. (2016, 4). Valuation of sitting and standing in metro trains using revealed preferences. *Transport Policy*, *47*, 94–104. doi: 10.1016/j.tranpol.2015.12.004

TRB. (2020a). *Developing a Guide to Bus Transit Service Reliability*. Washington, D.C.: Transportation Research Board. Retrieved from `https://www.nap.edu/catalog/25903` doi: 10.17226/25903

TRB. (2020b). *Minutes Matter: A Bus Transit Service Reliability Guidebook*. Washington, D.C.: Transportation Research Board. doi: 10.17226/25727

van Oort, N., Wilson, N. H. M., & van Nes, R. (2010, 1). Reliability Improvement in Short Headway Transit Services. *Transportation Research Record: Journal of the Transportation Research Board*, *2143*(1), 67–76. doi: 10.3141/2143-09

Yan, S., Zhou, J., & Zhao, Z. (2021). Expression and Validation of Online Bus Headways considering Passenger Crowding. *Journal of Advanced Transportation*, *2021*. doi: 10.1155/2021/4738177

Yan, Y., Liu, Z., & Bie, Y. (2016). Performance Evaluation of Bus Routes Using Automatic Vehicle Location Data. doi: 10.1061/(ASCE)TE.1943-5436

I acknowledge the use of ChatGPT [https://chat.openai.com/] to help brainstorm model options, translate concepts and phrases from my native language.

I entered the following prompt: "Come up with five model options that would help a master student explore the relation between crowding and headway variability in public transport."

I used the output as a starting point for generating ideas before narrowing down the topic for my assessment.

I also acknowledge the use of Elicit to create a map of the relations between the different papers reviewed for the literature research and to use the "snowball method" to find new references.