Estimation and Prediction of Urban Traffic Flows in Response to Global Pandemic Using Machine Learning and Foundation Models

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Abstract

Urban traffic flow refers to the dynamic movement of vehicles within a city, playing an important role in supporting sustainable and efficient transportation systems. This research concerns several methodological and empirical gaps related to urban traffic analysis, particularly in the context of data quality, model generalisability, and disruptions caused by external events such as the global COVID-19 pandemic. The aim of this research is to improve the understanding and prediction of urban traffic flows by integrating high-resolution sensor data, emerging urban indicators, machine learning and foundation models. Specifically, the research intends to achieve the following goals: (1) to develop a publicly available, long-term traffic flow dataset with high spatio-temporal granularity; (2) to explore how spatial distribution of built environment and socio-demographics influences traffic dynamics; and (3) to predict the temporal distribution of traffic flows under both normal conditions and disruptive events. The goals are achieved through three empirical studies conducted in Glasgow, UK.

To achieve the first objective, a high-resolution intra-city traffic dataset covering four consecutive years before, during, and after COVID-19 is constructed. A multi-step cleaning process is applied to remove poor-quality sensor records using spatial, temporal, and numerical filters. The filtered dataset is then validated through spatial and temporal analyses, including comparisons with government policy stringency measures during the pandemic. Results show that the dataset reliably captures daily, seasonal, and disruption-related variations in traffic flow across road types and neighbourhoods.

To achieve the second objective, the study integrates traffic flow data developed in the first study with a range of urban elements, including road characteristics, socio-demographics, surrounding built environments (land use and nearby points of interest), and the emerging urban big data source such as Google Street View (GSV) imagery. Spatial econometric models are used to understand the relationship between traffic flows and urban indicators before, during, and after pandemic periods. The results reveal that higher traffic flows are more frequently observed in areas with more young and white dwellers, while lower flows are observed in natural green spaces. Major roads between cities and towns also show heavier traffic flows. Besides, the application of GSV images in this research has revealed the heterogeneous effects of green space on urban traffic flows, as the magnitudes of their effects vary by distance. We also detect that the spatial dependence between adjacent neighbourhoods among the traffic flows and associated urban parameters is variable during

the four COVID-19 periods. With the influence of COVID-19, there has been a significant decrease in long-distance travel.

To achieve the third objective, two pre-trained foundation models, Lag-Llama and Chronos, are applied for zero-shot traffic flow prediction and we have compared their accuracy against traditional deep learning models. The results show that foundation models outperform deep learning models in traffic flow prediction under both normal conditions and disruptive events. Unlike deep learning models, which require large-scale historical data and extensive training time for each task, pre-trained foundation models can be directly applied to datasets with different data sizes, traffic dynamics, and context lengths. We also find that foundation models with longer context lengths and larger model sizes achieve higher prediction accuracy but require increased inference times. Selecting an appropriate foundation model is also crucial – models trained on a comprehensive dataset are more likely to achieve superior zero-shot performance, making them a practical and efficient choice for real-world traffic prediction applications.

Overall, this thesis contributes to the development of urban traffic research by introducing high-resolution traffic data, analysing the quantitative relationships between traffic patterns and urban elements, and demonstrating the potential of pre-trained foundation models for efficient and accurate traffic prediction using limited data. The findings can support urban planners and policymakers in making effective planning and resource allocation decisions in diverse and dynamically changing urban traffic environments.

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Acknowledgement

The day has finally come for me to write this acknowledgment.

As I sit before the blank page, memories from the past four years come vividly to mind. There are so many people I wish to thank. For me, this page does not mark the end of my PhD journey, but rather a moment of farewell.

I am deeply grateful to have had two outstanding supervisors during my time in Glasgow. They guided me with patience and wisdom, helping me find clarity even in the most difficult problems. Professor Qunshan Zhao encouraged me to attend numerous conferences, which allowed me to meet people from diverse backgrounds and broaden my horizons. Dr. Mingshu Wang's rigorous logic and clear thinking have left a lasting impression on me, shaping the way I approach research and learning.

There were also challenging times, and I owe much to my friends who stood by me. Zixin never tired of listening and comforting me. Xingyi's openness and cheerful spirit always lifted me from difficult moments. Jolin often brought me taro cake from a café, a gesture that warmed even the heaviest days. Zeo encouraged me with simple yet firm words: "Don't be sad anymore." My best friend, Xuerong, has always reminded me of the importance of caring for myself.

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Four years have passed quickly, and there remain regrets when I look back. Yet above all, I am profoundly thankful for everyone who has been part of my life during this journey.

Goodbye, or perhaps, until we meet again.

Author’s Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Chapter 1 Introduction

In most cities, the transportation system has been dominated by motor vehicles (Y. Li et al., 2024, 2025; Transport Scotland, 2019). Motor vehicles enhance mobility, broaden people's activity space, and support economic activities that would be difficult or impossible without them, making them a crucial component of urban life. However, the widespread use of motor vehicles has led to a range of urban challenges, including traffic congestion, air pollution, and road accidents (J. Lu et al., 2021; Rajé et al., 2018; S. Singh et al., 2023). These issues are affecting the daily lives of urban residents and reduce the sustainability of urban development (Karimi et al., 2022; X. Zhang et al., 2022). By 2019, the global number of motorised vehicles had reached 1.4 billion, representing a 40% increase since 2010 (S. C. Davis & Boundy, 2022, p. 40). While this growth reflects improved mobility and economic development, it has also intensified urban traffic-related problems. In the United Kingdom, the widespread use of motorised vehicles has made traffic congestion one of the most serious transport issues (Department for Transport, 2008). Meanwhile, motor vehicles are major consumers of fossil fuels (X. Zhu et al., 2021), which are the primary sources of urban air pollution and carbon dioxide emissions (W. Zhang et al., 2023). In Glasgow, approximately 350 deaths per year are attributed to air pollution (Urban Big Data Centre, 2022), highlighting the severe public health impacts of traffic-related emissions. With the ongoing transition to electric vehicles, these environmental and health impacts are expected to decrease gradually, but more progresses need to be made in the next decade. Additionally, road safety remains a critical concern, with around 1,600 fatalities recorded annually across the UK due to road accidents in 2024 (Department for Transport, 2024a).

Responding to these challenges requires an evidence-based understanding of how urban traffic flows are distributed across space, how they are shaped by the social and physical characteristics of urban neighbourhoods, and how they respond to external disruptions and policy interventions. Traditional transport demand modelling, including the four-step model, have been used as a foundational framework in transport planning practice (McNally, 2007; Ortúzar & Willumsen, 2011b). However, these frameworks were designed around assumptions of stable and repetitive travel behaviour, and struggle to capture the dynamic patterns of mobility that characterise contemporary urban environments. Research in transport geography has demonstrated that the distances, modes, and purposes of travel vary substantially across social groups, with significant consequences for access to employment, healthcare, education, and public services (Lucas, 2012; Lucas et al., 2016). For example, women tend to make more complex chained trip patterns linked to care responsibilities, which combine work trips with school drop-offs or visits to health services (Sánchez de Madariaga, 2013b). These travel patterns are poorly captured by traditional models designed around simple home-to-work commuting (Sánchez de Madariaga, 2013a).

However, the travel behaviour changed significantly during the Coronavirus disease 2019 (COVID-19) pandemic. In response to the crisis, the government implemented various social distancing measures to reduce the spread of SARS-CoV-2, particularly focusing on restricting human mobility in urban areas (Hadjidemetriou et al., 2020; T. Hu et al., 2021; M. Zhang et al., 2022). In the UK, human mobility was observed to decrease significantly after the nationwide lockdown implemented on 23 March 2020. This decline continued until the end of May 2020, with driving activity remaining approximately 60 percent lower compared to the same period in 2019 (Hadjidemetriou et al., 2020). In Glasgow, a total of 1.70 billion vehicle miles were travelled on roads in 2020, showing a 22% decrease compared to pre-COVID-19 levels (Department for Transport, 2023). Beyond the immediate decline in travel demand, the pandemic led to structural changes in mobility behaviour. These include the widespread adoption of hybrid working, reductions in long distance commuting and changes in peak hour travel patterns. Many of these changes have not fully reversed since restrictions were lifted. These developments highlight limitations in transport demand forecasting models that assume a return to pre-covid conditions. They also create a clear need for empirical evidence on how urban traffic systems respond to and recover from large scale external disruptions. At the same time, the pandemic period provides a unique natural experiment. A multi-year dataset covering traffic flows before, during, and after COVID-19 offers an opportunity to explore the resilience and adaptability of urban mobility systems under disruptive conditions in ways that no controlled study could replicate.

This thesis responds to these challenges by developing a comprehensive, data-driven analytical framework for understanding and predicting urban traffic flows in Glasgow across the COVID-19 pandemic period. Applying high-resolution traffic sensor data, spatial econometric modelling, and advanced time series foundation models, the research aims to provide both an empirical understanding of how urban physical and social factors shape traffic dynamics, and a more robust basis for traffic prediction under normal and disruptive conditions. This thesis builds on conceptual frameworks from the transport literature that emphasise accessibility and distributional impacts as key concerns of transport planning (Geurs & van Wee, 2004; Pereira et al., 2017) and contributes to the broader policy challenges of urban congestion management, transport equity, public health emergency planning, and the deployment of intelligent transport systems. The findings of this research are intended to be of direct relevance not only to the academic literature of transport geography, spatial econometrics, and machine learning, but also to the transport authorities, urban planners, and policymakers responsible for managing and investing in urban mobility systems in Glasgow and comparable cities.

The chapter then introduce the spatial and temporal characteristics of urban traffic flow, recognising that traffic patterns are influenced by both where and when travel occurs. This is followed by a discussion on Intelligent Transportation Systems and urban sensing technologies, which produce a variety of traffic-related data. In the context of data accessibility, this chapter introduces the importance of open, publicly available traffic flow data, including its value for transparency, reproducibility, and comparative urban studies. The chapter also explores the impact of the COVID-19 pandemic, which disrupted established mobility patterns but offering a unique opportunity to analyse traffic flow change under government mobility interventions. Finally, the chapter presents the research aims and questions that guide this thesis.

1.1 Urban Traffic Flow: A Critical Policy and Planning Challenge

Motor vehicles, as the most common mode of transport, offer complete freedom for travellers to transfer from one place to another according to the need and convenience (Transport, 2022). The UK is one of the five largest markets in Europe, accounted for 12.5% of the region’s total vehicle registrations (European Automobile Manufacturers Association, 2011). The total number of vehicles registered in Scotland has shown a steady upward trend over the longer term, with 3.1 million motor vehicles licensed in 2023 (Transport Scotland, 2025). In the same year, a total of 48.4 billion vehicle kilometres were driven across the country (Transport Scotland, 2024), with 35% of this distance travelled on urban roads, showing an overall increase of 24% since 2016 (Transport Scotland, 2019). Glasgow City recorded 3.63 billion vehicle miles travelled in 2023, making it the area with the highest total travel distance in Scotland (Transport Scotland, 2019).

However, with the popularisation of motor vehicles, the growing traffic congestion has become one of the most series transport problems facing the UK (Department for

Transport, 2008). In 2023, 12% of all journeys experienced delays caused by traffic congestion. Weekday travel was particularly affected during peak hours, with congestion delays occurring in 17–20% of journeys between 7:00 and 9:00 a.m., and 20–22% between 4:00 and 6:00 p.m. (Transport Scotland, 2025). Traffic congestion currently imposes an annual cost of £30.8 billion on the UK economy, with each motorist losing an average of £968 per year due to delays. With the Department for Transport predicting a potential 55% increase in traffic flows by 2040, strategic investment in infrastructure is becoming increasingly essential (Zsófia, 2025). What's worse, the usage of motor vehicles is accompanied with large consumption of fuels (X. Zhu et al., 2021). The Department of Energy and Climate Change estimates that 3.5 million tonnes of oil equivalent of petrol and diesel were consumed on Scotland's roads in 2022 (Transport Scotland, 2025). Fuel consumption has been rising steadily since 2013, with petrol and diesel remaining the primary sources of urban air pollution and greenhouse gas emissions (W. Zhang et al., 2023). In 2022, the road transportation accounted for 9.1 million tonnes of carbon dioxide equivalent (MtCO2e). This represents 22.1% of total net greenhouse gas emissions allocated to Scotland in the Greenhouse Gas Inventories, 9.1% higher than 2021 (Transport Scotland, 2025). Additionally, road safety remains a critical concern. In 2023, there were 155 fatalities and 1,944 people reported as seriously injured in road collisions across Scotland. Among them, 582 were child casualties, accounting for 10% of the total casualties across all age groups. The total economic cost of road collisions in 2023 is estimated at £1.189 billion (Transport Scotland, 2025).

To reduce the congestion, address air pollution, and create more pleasant and healthy places to live and work in, the UK government has introduced policy measures to promote sustainable transport and safer roads. For example, the Scottish Government published a new Road Safety Framework in 2021, outlining a vision for Scotland to achieve the world's best road safety performance by 2030. The framework highlights the long-term goal of Vision Zero, which aims to achieve zero fatalities and serious injuries on Scotland's roads by 2050 (Transport Scotland, 2021b). Besides, a congestion charge for driving in central London was introduced in 2003, and the scheme limited traffic entering the zone by 18% during weekday charging hours and reduced congestion by 30% in 2023 (Transport for London, 2023). Glasgow has introduced the Low Emission Zone as an essential measure, which has been enforced from 1st June 2023. All vehicles entering the city centre zone must meet the required emission standards (Glasgow City Council, 2024a). This measure aims to not only improve air quality and protect public health, but also encourage more sustainable transport options.

Considering the large impacts of motor vehicle use, the urban traffic flow studies have been a crucial area for researchers, city planners and policymakers for decades (Batty, 2008; Y. Li et al., 2024; Maerivoet & Moor, 2005; Y. Pan et al., 2024). As a direct representation of how, when, and where motor vehicles travel through urban areas, traffic flow data serves as an important indicator of urban transport efficiency and the demand for human mobility (Golob et al., 2008; M. Guo et al., 2021; Kalair & Connaughton, 2021). Additionally, traffic flow analysis contributes to the assessment of transport emissions (Jamshidnejad et al., 2017; K. Ma et al., 2021; L. Xia & Shao, 2005; Yao et al., 2021), helps identify traffic congestion patterns (Kohan & Ale, 2020; Treiber & Kesting, 2012; Zang et al., 2023), and supports the evaluation of policy measures, such as low-emission zones (Ceccato et al., 2024; Shin et al., 2024; Zhai & Wolff, 2021).

Beyond the immediate benefits of improved traffic management, studying traffic flow also provides critical insights into the socio-economic dynamics of urban life (Fattah et al., 2022; Krasnikov et al., 2024). Research in transport geography and urban studies has shown that mobility patterns reflect social inequalities in access to employment, healthcare, education, and public services. These inequalities are shaped by socio-economic position, gender, ethnicity, age, and caring responsibilities (Lucas, 2012). Transport poverty refers to the condition in which individuals are unable to access the transport required to participate fully in social and economic life. This condition affects a significant proportion of urban residents, particularly people in low-income households, older adults, and those with caring responsibilities (Lucas et al., 2016). Women's travel patterns are often characterised by shorter and more complex trips that involve multiple destinations. These patterns are closely linked to care and domestic responsibilities. However, such travel behaviours are often underrepresented in transport models and planning frameworks that prioritise peak hour commuting (Sánchez de Madariaga, 2013b). Traffic flow patterns are also associated with socio-demographic factors such as population density, ethnic composition, and age structure, revealing spatial disparities in mobility and transport infrastructure (Klinger & Lanzendorf, 2016; Y. Li et al., 2024). Moreover, analysing long-term traffic flow patterns provides valuable insights for forecasting future demands on urban transport systems, particularly under the conditions of rapid urbanisation, (Y. Zhang et al., 2020) climate change (Krasnikov & Mironov, 2024; Medina-Salgado et al., 2022), and unexpected disruptions such as pandemics (Ghanim et al., 2022; Liapis et al., 2021; Svabova et al., 2024). With the development of technologies such as remote sensing, machine learning, and smart sensor networks, the availability and spatial-temporal granularity of traffic flow data have greatly improved (Y. Li et al., 2024, 2025). These high-resolution datasets play a critical role in developing efficient transport systems and promoting sustainable urban development (Ba et al., 2024).

1.2 Spatial and Temporal Dimensions of Urban Traffic Flows

Motor vehicles traveling from one place to another in cities generate urban traffic flows. At every point in time, a vehicle occupies a specific position in space, illustrating the spatial and temporal nature of traffic dynamics (Teodorović & Janić, 2017a). For example, a trip by car from home to university can be represented as a series of time points and corresponding spatial positions, highlighting how traffic flows can be mapped and analysed across both dimensions (Teodorović & Janić, 2017a). Traffic flows are not static; they vary across different locations and change over time (Teodorović & Janić, 2017b). Spatial variations are largely driven by people undertaking various economic, business, cultural, touristic, sport, and recreational activities (Teodorović & Janić, 2017a) in different urban areas, while temporal changes are influenced by factors such as the time of day, day of the week, and special events. These variations can be systematically studied by collecting and analysing appropriate traffic flow data (Teodorović & Janić, 2017b) across space and time, providing insights into the underlying mechanisms of urban mobility. Understanding these spatial and temporal dimensions is essential for transport planning and policy. The effectiveness of interventions such as congestion charges, low emission zones, and public transport investment depends on where and when traffic is concentrated.

Spatial variations in urban traffic flows are influenced by how people engage in different activities across the city (Teodorović & Janić, 2017a). These activities, ranging from economic and business pursuits to social engagements (Teodorović & Janić, 2017a), are closely related to the spatial distribution of land use types (Izanloo et al., 2017; ping, 2012; L. Sun & Liu, 2023), points of interest (POIs) (L. Chen et al., 2022; Z. Su et al., 2024; H. Zeng et al., 2022), road characteristics (L. Chen et al., 2022; Z. Wang et al., 2025), and social demographics (Alves & Cordeiro, 2021; Dostál & Havlí, 2010). For instance, residential neighbourhoods, commercial centres, industrial zones, and recreational areas generate varying traffic patterns based on their specific functions (Izanloo et al., 2017; Næss, 2005). Areas with high concentrations of workplaces, such as central business districts, typically experience heavy traffic flows during the morning and evening rush hours (Järv et al., 2012). Conversely, places with tourist attractions, shopping malls, and entertainment venues generate traffic flows during leisure times, such as weekends or holidays (W. Huang et al., 2019; SCHLICH et al., 2004). The road network also plays a significant role in spatial traffic patterns, with highways, arterial roads, and local streets exhibiting different traffic flow characteristics (Y. Li et al., 2024). Socio-demographic factors, such as population density (Dostál & Havlí, 2010) and income levels, further shape traffic flows, as wealthier, more densely populated areas tend to see higher car ownership and more frequent vehicle movements (Y. Li et al., 2024).

Temporal variations in urban traffic flows reflect the regular patterns of daily life and the timing of social and economic activities (Schönfelder & Axhausen, 2016). As with spatial variations, temporal changes are influenced by people’s economic, cultural, and recreational activities throughout the day and week (W. Huang et al., 2019). One of the most noticeable temporal features is the presence of daily peaks, commonly known as rush hours, which occur in the morning and evening as people commute to and from work, school, or other activities (Järv et al., 2012). Weekly cycles are also clear, with weekdays generally characterised by structured commuting patterns, while weekends see increased traffic flows related to leisure, shopping, and recreational activities (SCHLICH et al., 2004). In addition to regular cycles, extraordinary temporal variations are caused by large events such as public holidays and COVID-19 pandemic, which can lead to sudden and significant fluctuations in local traffic flows (Grassi & and Díaz, 2024; X. Liu & Li, 2022; Nie et al., 2024).

Interpreting these spatial and temporal patterns requires conceptual frameworks that go beyond simple description. Geurs and van Wee (2004) argue that accessibility is a meaningful measure of transport system performance and note that evaluating accessibility requires attention to both the spatial distribution of land uses and the temporal availability of transport services. Pereira et al. (2017) further argue that transport planning frameworks must explicitly consider distributional impacts. This perspective recognises that the benefits and costs of transport systems are unevenly distributed across social groups and geographic areas. These conceptual perspectives inform the analytical framework of this thesis. The research aims to develop a spatial and socially grounded understanding of urban traffic flows that can better support equitable and evidence based transport policymaking.

1.3 Traffic Flow and Urban Sensing Technologies

Traffic flow, typically measured in vehicles per unit time, is one of the fundamental variables monitored by Intelligent Transportation Systems (Kühne, 2008). Measurements of traffic flow can be performed at a specific point on the road, over a stretch of road, or simultaneously from multiple motor vehicles across a wide area. The most commonly used technology for point-based measurements is the inductive loop detector. This technology has been in use since the 1960s, with the electronics buried in the road surface. When a motor vehicle passes over the loop, the metal of the vehicle disrupts the magnetic field, causing a change in the loop's inductance. This change continues until the vehicle leaves the detection zone (Teodorović & Janić, 2017b).

The Split Cycle Offset Optimisation Technique (SCOOT) system is the major adaptive traffic control programme in use in the UK (Department for Transport et al., 2019). It was developed by the Transport Research Laboratory (TRL) in collaboration with UK traffic systems suppliers (Hunt et al., 1981). SCOOT is adaptive and responds automatically to traffic fluctuations, making it an effective and efficient tool for managing traffic on signalised road networks (Department for Transport, 1999). It is now used in over 170 towns and cities in the UK and overseas. The most common sensors used by SCOOT are those buried in the road surface, such as inductive loop detectors, or mounted above ground, typically on top of the signal post, such as microwave vehicle detectors (Department for Transport et al., 2019). Inductive loop detectors collect traffic flows by analysing the electromagnetic effects caused by the presence or passage of a vehicle (Y. Li et al., 2025). Specifically, when a vehicle passes the inductive loop, SCOOT converts the information into a “link profile unit” (LPU), which is a hybrid of traffic flow and occupancy. The unit used by SCOOT in its calculations is called “cyclic flow profiles”, which are the LPU signals over time that are constructed for each link (Department for Transport, 1999).

Traffic flow can be extracted from the “cyclic flow profiles” and is typically expressed in vehicles per unit time, such as vehicles per minute or vehicles per hour. The choice of time unit for measuring traffic flow depends on the specific application, spatial and temporal resolution required. For example, short intervals like 30 seconds or 1 minute are commonly used in adaptive traffic control systems (Q. Jia et al., 2024; D. Wu et al., 2024; K. Wu et al., 2023; Z. Xia et al., 2024) to detect rapid fluctuations in traffic conditions and to support real-time traffic signal adjustments. In contrast, longer intervals such as 15 minutes, 1 hour, or peak periods are often applied in traffic analysis and prediction (Alvi et al., 2024; W. Lu et al., 2024; J.-D. Wang & Susanto, 2023; D. Yang & Lv, 2023). On a broader timescale, researchers frequently use averaged traffic flow values to represent typical traffic patterns over long periods. One of the most widely used metrics is the Annual Average Daily Traffic (AADT), which is calculated by dividing the total number of vehicles passing a specific point over a full year by 365 (Molugaram & Rao, 2017). The AADT serves as a standard indicator in transportation planning (Castro-Neto et al., 2009; Huynh et al., 2021) and infrastructure design (D. C. Han, 2024; Lako & Gjevori, 2024). However, the period of actual observation is often shorter than a full year (Teodorović & Janić, 2017b). In such cases, Average Daily Traffic (ADT) or Average Weekly Traffic are used as more practical indicators, providing estimates of typical daily or weekly volumes based on the available data (Molugaram & Rao, 2017).

1.4 Open Traffic Flow Data

In recent years, the global push for open government data has transformed the way urban mobility is understood and managed. Based on the principles of transparency and accountability, open data policies have encouraged public institutions to release datasets collected through taxpayer-funded initiatives (Fitzgerald et al., 2013; Jethani & Leorke, 2021; Koznov et al., 2016; McDermott, 2010; Shelby, 2000). These policies have laid the groundwork for the public availability of large-scale transport and traffic datasets, including those related to traffic flows, congestion patterns, and road infrastructure.

In the UK, open data policy is supported by the National Data Strategy (Department for Digital, Culture, Media and Sport, 2019) and the National Action Plan for Open Government (2024–2025) (Cabinet Office et al., 2023). These documents reaffirm the government's commitment to publishing public sector datasets under the Open Government Licence (OGL) (The National Archives, 2014). The *Data.gov.uk* (The Government Digital Service, 2010) platform serves as the primary portal for accessing these resources, including traffic flow records, infrastructure inventories, and transport survey data collected by departments and local authorities. In the United States, the Open Government Directive, launched in 2009, marked a significant policy shift towards transparency and public data sharing (Orszag, 2009). This was operationalized through *Data.gov* (U.S. Government, 2009), which provides access to a large range of datasets, including those from the Department of Transportation and city-level open mobility platforms. Similar frameworks have been adopted across Europe. France established

Data.gouv.fr (French Government, 2015) under the coordination of Etalab (*Etalab – Public Data Policy*, 2019), releasing thousands of datasets from national and local governments. For mobility-specific data, *Transport.data.gouv.fr* (French Government, 2019) offers datasets in partnership with the General Directorate for Infrastructure, Transport and Mobilities, supporting public access to traffic, infrastructure, and transport services information. Finland enacted the Act on Transport Services (Ministry of Transport and Communications, 2017), requiring transportation operators to provide data via open APIs. Estonia's Open Data Action Plan (Republic of Estonia Government, 2021) integrates annual goals for improving access to transport and mobility datasets, while Denmark has introduced legal measures to ensure public access to administrative data and publicly funded research (Ministry of Digital Government, 2019).

Building on these national portals and open data strategies, many governments and local transport authorities have also launched domain-specific platforms focused exclusively on traffic and mobility data collected at the sensor level within specific cities or regions. In the United States, the New York City Department of Transportation (NYC DOT) provides open access to historical vehicle counts via its Automated Traffic Volume Counts portal (New York City Department of Transportation, 2024). It uses Automated Traffic Recorders (ATR) to collect traffic sample volume counts at bridge crossings and roadways at 15-min interval. The California Performance Measurement System (PeMS) (California Department of Transportation, 2025a) offers one of the most comprehensive collections of freeway data, including minute-level traffic flow, speed, and travel time data across the state. The traffic data is collected in real-time from over 39,000 individual sensors across all major metropolitan areas of the State of California (California Department of Transportation, 2025b). In the UK, Glasgow City Council publishes real-time traffic flow data through the Glasgow Open Data portal (Glasgow City Council, 2022; Y. Li et al., 2025). This data is collected via a network of SCOOT system sensors installed at more than 1,200 locations across the city (Glasgow City Council, 2023). Glasgow Open Data portal also provides historical traffic flow data since 2018 (Glasgow City Council, 2022).

1.5 The COVID-19 Disruption: A Natural Experiment and Policy Challenge

The COVID-19 pandemic brought about a significant and abrupt transformation in urban mobility, offering a unique natural experiment to observe how transport systems respond to large-scale external disruptions. In the UK, the national government implemented a range of public health measures to contain the virus, including mobility restrictions, social distancing guidelines, and the closure of schools and workplaces (Burton et al., 2023; Gore et al., 2021; Jarvis et al., 2021; Keightley et al., 2023). These interventions significantly changed daily travel behaviour and urban traffic dynamics (Abduljabbar et al., 2022; Harrington & Hadjiconstantinou, 2022; Paul et al., 2022).

In Glasgow, motor vehicle usage declined significantly in response to COVID-19 restrictions and lockdowns. In 2020, road traffic in the city dropped to 1.70 billion vehicle miles, representing a 22% decrease compared to 2019 levels (Department for Transport, 2023). Particularly, traffic flow began to decrease even before the full lockdown was implemented. Following the government's advice on March 16th to work from home where possible, average traffic flow during the morning and evening peak periods dropped by approximately 14%. This reduction deepened to around 37% immediately after the national lockdown was officially announced on March 23rd (J. Hong, 2020). Mobile location data provides further insight into the scale and nature of these behavioural changes. Google Community Mobility Reports (Community Mobility Reports, 2022), derived from aggregated mobile phone location history, show that in Glasgow, trips for retail and recreation purposes dropped by 84% compared to pre-pandemic levels. These data are unique in that they capture real-world changes in traffic dynamics and directly reflect how urban traffic systems responded to unprecedented conditions, rather than simulated or hypothetical scenarios.

The policy implications of these changes extend well beyond the pandemic period itself. The availability of high-resolution traffic flow data before, during, and after the pandemic enables detailed temporal analyses of system performance and behavioural change (Y. Li et al., 2025), providing an empirical basis for evaluating the transport impacts of public health interventions and informing the design of future emergency response frameworks. This dataset allows in-depth analyses of peak and off-peak trends, seasonal and annual variations, as well as congestion patterns shaped by stringent mobility restrictions (M. Lee et al., 2020; Y. Pan, Darzi, et al., 2020). It represents the conditions that occurred, contributing to understanding disruptions and preparing for future uncertainties (Y. Li et al., 2024). This disruption also presents a unique opportunity to study both the resilience and adaptability of transport systems under crisis conditions (Bubicz et al., 2023; Chakwizira, 2022). Researchers can assess how quickly traffic patterns changed in response to policy announcements, how different areas or road types were affected, and how mobility systems recovered once restrictions were lifted (Santana-Cibrian et al., 2020;

Thombre & Agarwal, 2021). Beyond the immediate response, the COVID-19 period also offers insights into the long-term viability of alternative travel behaviours, such as remote working and modal shifts (M. Abdullah et al., 2020; Currie et al., 2021; Z. Huang et al., 2023). It challenges urban planners and policymakers to consider which of these temporary adaptations may inform future efforts to build more sustainable, flexible, and resilient mobility systems (Campisi et al., 2020; Griffiths et al., 2021; Kakderi et al., 2021). Researchers, city planners, and transportation agencies can use the COVID-19 dataset to inform long-term strategies, infrastructural adjustments, and adaptive management approaches (Afrin et al., 2021; Wallentin et al., 2020).

1.6 Research Aim and Objectives

Urban traffic flows are influenced by a combination of physical, social, and temporal factors, and are affected by external disruptions such as the COVID-19 pandemic. Understanding how traffic flows are distributed across space, how they respond to changing urban conditions and policy interventions, and how they can be accurately predicted under both normal and disruptive conditions are questions of fundamental importance to transport geography, urban planning, and the design of intelligent transport systems. Existing research faces limitations in data quality and temporal coverage, and traffic prediction models were not designed to handle behavioural changes associated with large scale disruptions. This thesis addresses these limitations through an integrated empirical study of urban traffic flows in Glasgow before, during, and after the COVID-19 pandemic, based on high resolution traffic sensor data, spatial econometric models, and advanced time series foundation models. The aim of this research is to develop a comprehensive evidence-based understanding of the spatial distribution, socio-environmental determinants, and temporal dynamics of urban traffic flows under both normal and disruptive conditions, and to evaluate the potential of emerging prediction models to support adaptive and resilient urban transport planning and policy. Empirical studies will be carried out using the data from Glasgow, UK. Specifically, three objectives are to be achieved through this research:

- Research objective 1: to explore the spatial and temporal characteristics of urban traffic flows in Glasgow across four consecutive years covering the COVID-19 pandemic, by constructing and validating a high resolution, city scale traffic flow dataset that captures hourly flow patterns across all road types before, during, and after the pandemic period. This objective contributes to the transport geography and urban mobility literature by providing an empirically based analysis of intra-city traffic dynamics across space and time, and by establishing the evidential foundation necessary for the spatial and temporal analyses pursued in subsequent objectives.

- Research objective 2: to understand the quantitative relationship between the spatial distribution of urban physical and social elements (i.e., built environment, socio-demographics) and traffic dynamics by using new forms of urban big data and high spatio-temporal traffic flow data in Glasgow, before, during and after the COVID-19 pandemic. This objective contributes to the spatial econometrics and urban big data literature by revealing changes in the spatial dependence between traffic flows and urban indicators in response to mobility restrictions. It also contributes to the public health and emergency planning literature by providing evidence on the role of different urban contexts in mediating the traffic impacts of pandemic period policy interventions.

- Research objective 3: to evaluate the performance of deep learning models and time series foundation models in predicting urban traffic flows under both normal conditions and disruptive events in Glasgow. This objective contributes to the machine learning and time series prediction literature by providing a systematic empirical comparison of deep learning models and emerging foundation models in a real world, multi-year urban traffic context. It also contributes to the smart cities and intelligent transport systems literature by assessing the practical viability of zero-shot foundation model prediction as a basis for adaptive traffic management under both normal and disruptive conditions.

1.7 Structure of the Thesis

This thesis is structured into seven chapters. The current chapter introduces the background of the proposed study as well as the research aim and objectives.

Chapter 2 presents a comprehensive literature review that establishes the theoretical and empirical foundations for the thesis. The chapter is structured into four main sections. The first reviews the literature on travel behaviour and mobility constraints, exploring theoretical perspectives on how and why people travel, and discussing how mobility patterns are socially differentiated across population groups. This section pays particular attention to the underrepresentation of disadvantaged groups in conventional transport planning frameworks, including the complex care-related trip patterns of women and the mobility constraints faced by transport-poor households. The second section reviews transport demand modelling approaches, describing the evolution from the classical four-step model through discrete choice models and activity-based models to traffic flow models, while identifying the limitations of these frameworks in capturing dynamic and disruption-driven behavioural change. The third section introduces the conceptual frameworks that inform the empirical analyses of this thesis, focusing on the relationship between the urban built environment and travel behaviour, and on accessibility and spatial equity as organising principles for evaluating transport system performance. The fourth section reviews the influential factors shaping urban traffic flows across spatial and temporal dimensions, including road characteristics, socio-demographics, land use, points of interest, street-level imagery, time of day, day of the week, seasonal variations, special events, government policies, and traffic accidents. Finally, the chapter concludes by identifying research gaps, and these gaps serve to position this thesis's empirical contributions.

Chapter 3 presents a systematic review of the methodologies available for analysing and predicting urban traffic flows, providing the analytical foundation for the empirical studies presented in Chapters 5 and 6. The chapter is structured into two main sections. The first section reviews regression methods for analysing the determinants of urban traffic flows, beginning with linear regression models and their limitations in the context of spatially structured urban data. The section then reviews spatial regression models including the Spatial Lag Model, Spatial Error Model, and Spatial Durbin Model, which explicitly account for spatial dependence and spatial heterogeneity between neighbouring observations. The second section reviews temporal models for predicting traffic flows, structured into four sub-sections covering statistical time series models, machine learning models, deep learning models, and emerging large language models and foundation models. The review outlines the evolution from traditional statistical models towards data-driven and generalisable prediction models, evaluating the capacity of each model to capture both short-term fluctuations and long-term dependencies in traffic flow time series. The chapter concludes by identifying the methodological gaps that motivate the selection of the Spatial Durbin Model for the spatial analysis in Chapter 5 and the comparative evaluation of deep learning and foundation models for traffic forecasting in Chapter 6.

Chapter 4 focuses on the first research objective — introducing a long-term traffic flow dataset at an intra-city scale with high spatio-temporal granularity. The raw traffic flow data are collected through the Glasgow open data portal. To refine the dataset, a two-fold filtration process based on spatial and temporal constraints is implemented. Initially, data is filtered according to the sensors placed, narrowing the scope to specific geographical areas and locations. Subsequently, a temporal constraint is applied to refine the dataset based on the study period and 15-minute intervals. Then, the statistical information in the records for the remaining sensors is examined. In this dataset, each record refers to the traffic flows captured by the sensors at one-time intervals. Sensors with a substantial proportion of irregular traffic flows or incorrect time intervals are excluded from the dataset. The final step involves reconstructing and aggregating the cleaned traffic flow data. This process ensures that the data adheres to the specific time intervals and formatting requirements, resulting in an accurate and reliable dataset for downstream applications.

Chapter 5 focuses on the second research objective — understanding the relationship between urban parameters and traffic flows across the COVID-19 pandemic in Glasgow. This chapter uses the spatial Durbin model to understand the relationship between traffic flows, urban infrastructure, and socio-demographic indicators before, during, and after pandemic periods. Factors such as road characteristics, socio-demographics, surrounding built environments (land use and nearby points of interest), and the emerging urban big data source of Google Street View images are included to understand their influences on time series traffic flows.

Chapter 6 focuses on the third research objective — predicting traffic flows in Glasgow under both normal conditions and disruptive events. This chapter applies two foundation models, Lag-Llama and Chronos, for zero-shot traffic flow prediction and compare their accuracy against traditional deep learning models. Prediction experiments are conducted using both the complete dataset and a post-COVID-19 subset to assess model robustness under different traffic scenarios. Multiple context lengths (input time windows) are tested to examine the sensitivity and adaptability of each model.

Chapter 7 summarises the main findings and contributions of this research to the field of urban traffic flow analysis. It discusses the results in relation to the research objectives, outlines the methodological and policy implications, and reflects on the study’s limitations. The chapter concludes by offering recommendations for future research and directions for continued development in spatiotemporal modelling and traffic prediction.

Chapter 2 Literature Review

Understanding urban traffic flow requires exploring multiple interconnected dimensions: the behaviours and constraints of individual travellers, the mechanisms through which individual choices aggregate into system-level demand, and the urban contexts that shape both individual mobility and aggregate flow patterns. This literature review aims to provide a resource for researchers and practitioners in urban mobility analysis by: 1) reviewing people's behaviour in transport and the constraints they face in mobility in cities, 2) exploring transport demand modelling approaches that predict human travel behaviour in urban systems, 3) establishing conceptual frameworks that provide theoretical foundations for exploring traffic-urban context relationships, 4) identifying specific factors influencing urban traffic flows.

2.1 Travel Behaviour and Mobility Constraints

Living, working, shopping and recreating are spatially separated activities (Van Acker et al., 2010). To participate in these activities, people may travel using various modes. However, the ability to travel and participate in activities is not uniform across populations. Different individuals and social groups face varying constraints on their mobility (Chapin, 1974), shaped by time budgets, care responsibilities, economic resources, and transport availability (Kenyon et al., 2002; Wigan & Morris, 1981). Understanding these behavioural patterns and mobility constraints is essential for comprehending how travel demand is generated and distributed across urban space and time. This section reviews literature on travel behaviour and the constraints people face in urban mobility, exploring both general theoretical frameworks and the specific experiences of populations who face systematic mobility disadvantages.

2.1.1 Theoretical Perspectives on Travel Behaviour

Nowadays, travel is generally considered as a derived demand (Mokhtarian & Salomon, 2001). Although sometimes people might travel just 'for fun', they mainly travel to access desired activities in different places. This is because activities such as living, working, shopping and recreation are in most cases spatially separated, thereby generating the need for travel (Van Acker et al., 2010; van Wee, 2009). Activity-based approaches represent a key theoretical advancement recognising that travel serves to connect activities distributed across urban space (Axhausen & Gärling, 1992; Ettema & Timmermans, 1997). Rather than analysing single journey purposes, activity-based frameworks explore how individuals schedule and chain multiple activities throughout the day, with travel serving as the necessary link between activity locations. This approach acknowledges that travel decisions are interdependent (Damm, 1980): the choice of when and where to work influences subsequent choices about shopping, childcare, or leisure activities.

Complementing the activity-based perspective, time geography (Hägerstrand, 1970) emphasises that individuals operate within space-time constraints. Those constraints fundamentally shape what activities and travel are feasible. Hägerstrand identified three types of constraints that influence individual’s travel behaviour: capability constraints (physiological necessities such as sleep and eating, as well as physical mobility limitations), coupling constraints (the need to be in specific places at specific times for activities involving others, such as work meetings or school schedules), and authority constraints (access restrictions based on laws, opening hours, or social norms). These constraints create individual "space-time prisms" that define the set of locations a person can feasibly reach given their activity commitments and mobility capabilities (Kwan et al., 2015). Time geography reveals that observed travel patterns reflect not just preferences, but the interplay of needs, opportunities, and constraints operating within individuals' daily space-time budgets.

Building on these foundations, research has explored trip chaining, which refers to the linking of multiple trip purposes into continuous journeys rather than making separate home-based trips for each activity (Thill & Thomas, 1987). Trip chaining behaviour reflects individuals' strategies for efficiently organising activities within time constraints (Kondo & Kitamura, 1987). For example, rather than returning home between work and shopping, individuals may chain these activities together to minimise total travel time. The prevalence and complexity of trip chaining vary across populations and are influenced by factors such as employment patterns, household composition, care responsibilities, and transport mode availability (McGuckin & Murakami, 1999).

2.1.2 Socially Differentiated Mobility Patterns

While the theoretical frameworks above provide important insights into travel behaviour generally, a substantial body of research demonstrates that mobility patterns and constraints are not uniform across social groups (Paola, 2007; Uteng, 2009; van Wee, 2009). Gender, care responsibilities, income, and other dimensions of social difference fundamentally shape who travels, when, where, how, and under what constraints.

2.1.2.1 Care Trips

Sánchez de Madariaga (2013a) has demonstrated that women's travel behaviour mobility patterns differ systematically from men's, primarily due to disproportionate care responsibilities within households. Women are more likely to make trip chains that combine multiple purposes, such as work commutes that are intertwined with childcare, shopping, and elder care activities, often within tight time constraints. For instance, a typical journey might involve traveling from home to drop children at school, continuing to work, leaving work mid-day for a medical appointment with an elderly parent, picking up groceries, and collecting children from after-school activities before returning home.

These complex journey patterns differ fundamentally from the traditional direct commute model. Research has documented that women make more trips per day on average than men, but these trips are shorter in distance and more likely to be multi-purpose (Gauvin et al., 2020). Women's trips are also more dispersed spatially (Schwanen et al., 2008), meaning they are not concentrated on direct routes between home and employment centres, and they occur across a broader time window throughout the day rather than during conventional peak periods.

The complexity of care-related travel creates particular constraints. Trip chaining requires precise temporal coordination, as each activity in the chain has specific time windows (school drop-off times, work schedules, shop opening hours) (Kwan, 2000; Sánchez de Madariaga, 2013a). This creates tight coupling constraints in Hägerstrand's terms: missing one scheduled activity can cascade into conflicts throughout the remainder of the day. Women engaged in complex care-related trip chains therefore face reduced flexibility and are particularly vulnerable to disruptions such as transport delays or unexpected schedule changes (Schwanen et al., 2008).

Furthermore, the modes available for complex trip chains differ from those suitable for simple commutes. Complex trip chains often require multiple modes or transfers. Because care trips are frequently chained, they "rely on more than one mode of transport" to complete different stages of the journey. This can include combinations of walking, buses, subways, taxis, and sometimes cars (Sánchez de Madariaga, 2013b). The modal challenges of care travel are compounded by gendered differences in transport access. Women generally have less access to a car than men and are the main users of public transport. While income levels can increase access to a private vehicle, the "material impossibility" of combining work and care often stems from the lack of suitable transport provided by the current system rather than simply economic constraints (Sánchez de Madariaga, 2013a). Public transport systems designed around peak-hour commutes to central employment areas frequently fail to accommodate the dispersed, multi-stop, and off-peak nature of care-related travel, making complex trip chains difficult to execute even when public transport options technically exist.

2.1.2.2 Transport Poverty

Beyond gendered differences in travel patterns, significant portions of urban populations face more fundamental barriers to mobility. Lucas (2012) conceptualises transport poverty as the inability to access essential goods, services, and social networks due to transport disadvantage. This disadvantage manifests in multiple forms: mobility poverty (systemic lack of transport services or infrastructure), accessibility poverty (difficulty of reaching key destinations within a reasonable time, ease, and cost), transport affordability (lack of financial resources to pay for transport), and exposure to transport externalities (disproportionate exposures to the negative effects of the transport system, such as air pollution, noise, and traffic accidents) (Lucas et al., 2016). Transport poverty differs from general poverty in important ways (Mattioli et al., 2017). Individuals may have adequate income for basic needs but still face mobility barriers due to poor transport provision in their residential locations, particularly when rising rents force them to less central areas (Bailey et al., 2025). Conversely, some households experience “forced car ownership,” meaning they maintain vehicles despite financial strain because no viable alternatives exist for accessing employment and essential services (Lucas et al., 2016). The costs of forced car ownership can consume substantial portions of household income, creating financial stress while simultaneously being unavoidable given spatial and temporal constraints on accessing opportunities.

The spatial dimensions of transport poverty are well-documented. Transport disadvantage concentrates in peripheral urban areas (Lucas, 2012), often in social housing estates or lower-income neighbourhoods with poor public transport provision and limited local amenities (Mattioli et al., 2017). These areas may have been developed during periods when car ownership was assumed universal, or may have experienced service reductions or fare increases well above the rate of inflation (Curl et al., 2018). Residents face a spatial mismatch: employment and services are concentrated elsewhere, requiring travel, but transport options are limited and expensive (Lucas et al., 2016). Research has also identified temporal dimensions of transport poverty (Lucas, 2012). Low-income workers are disproportionately employed in shift work, evening, or weekend positions—precisely when public transport service is reduced or unavailable (Curl et al., 2018; Blumenberg & Pierce, 2014). For households without private vehicles, this temporal mismatch between work schedules and transport availability creates severe constraints. Some workers may be excluded from certain employment opportunities entirely due to transport unavailability, while others face very long journey times (Jahanshahi et al., 2015) requiring multiple transfers or reliance on informal transport arrangements.

The intersection of multiple constraints creates particularly acute mobility disadvantage for certain populations. Single parents, especially mothers (Curl et al., 2018), face combined pressures of care responsibilities (requiring complex trip chaining), time poverty (limited hours available for travel), and often economic constraints (limited budgets for transport). Similarly, elderly populations may face physical mobility limitations, reduced incomes, and residence in areas with declining transport service (Lucas, 2012; Schwanen et al., 2012). These intersecting constraints create situations where the space-time prisms of feasible activity participation become severely restricted.

2.2 Transport Demand Modelling

Understanding individual travel behaviour and mobility constraints, as discussed in the previous section, provides essential insights into why people travel. However, translating these individual-level behaviours into predictions of aggregate travel demand across urban networks requires formal modelling frameworks. Transport demand modelling serves as the analytical bridge between individual travel behaviour and observed traffic patterns in urban systems. This section reviews the evolution of transport demand modelling approaches, exploring both choice models that capture individual decision-making processes and traffic flow models that represent the aggregate movement of motor vehicles through networks.

2.2.1 The Four Step Model

Transport demand modelling has undergone significant conceptual and methodological evolution over the past several decades. The four-step model, first applied in the early 1950s (Weiner, 2016), decomposed travel demand estimation into sequential stages: trip generation (how many trips originate from and are attracted to each zone), trip distribution (where trips go), mode choice (which transport mode is used), and trip assignment (which routes are taken) (Profillidis & Botzoris, 2019). While this framework provided a primary tool for forecasting travel demand, it typically operates as a series of independent stages where total demand is fixed before route assignment, relying on aggregate data at the zonal level rather than representing underlying individual travel behaviour (McNally, 2007).

Critiques of the four-step model motivated significant theoretical and methodological advances (McNally, 2007). Researchers highlighted that the sequential structure ignored interdependencies between decisions, for instance mode choice and destination choice are often made jointly rather than sequentially. The reliance on aggregate zonal data obscured heterogeneity in travel behaviour across individuals and failed to capture the activity-based nature of travel. Furthermore, the four-step model's focus on commute trips during peak periods neglected the diversity of trip purposes, timings, and complexities such as trip chaining. These limitations led to the development of disaggregate choice models and activity-based modelling frameworks. These approaches shift the focus from trips to activity participation, more explicitly capturing underlying travel behaviour and daily activity patterns. Rather than predicting aggregate flows between zones, these approaches model individual travel choices, including destinations, modes, routes, and departure times, as functions of individual and household characteristics, travel costs and times, and attributes of available alternatives (Bowman & Ben-Akiva, 2001a). The outputs of individual-level models can then be aggregated to generate network-level demand predictions, providing a more behaviourally grounded foundation for transport forecasting.

2.2.2 Discrete Choice Models

Discrete choice models have become the powerful framework for representing individual travel decisions in transport demand modelling (Bierlaire, 1998). These models are grounded in random utility theory, which posits that individuals choose among discrete alternatives (e.g., transport modes, destinations, routes) to maximise their utility, subject to the information and constraints they face (McFadden, 1974b; Train, 2009).

2.2.2.1 Random Utility Theory and the Multinomial Logit Model

The foundational concept in discrete choice modelling is that each individual associates a utility with each available alternative and chooses the one with the highest utility. This utility is decomposed into a representative (observable) component and a stochastic (random) component (McFadden, 1974a). The representative component is defined as a function of the attributes of the alternatives and the characteristics of the individual. The stochastic component captures unobserved factors, such as variations in taste or measurement errors, that influence the final choice.

The multinomial logit (MNL) model is a widely used probability model for discrete response (McFadden, 1987). It assumes that random utility components are independently and identically distributed according to a Gumbel (extreme value Type I) distribution, leading to a closed-form expression for choice probabilities (McFadden, 1974a). The probability that an individual chooses alternative *i* is defined by the ratio of the exponentiated utility of alternative *i* to the sum of exponentiated utilities of all available alternatives. This formulation is computationally tractable, offers a clear behavioural interpretation of choice axioms, and is estimated using maximum likelihood methods. MNL models have been extensively applied to mode choice, destination choice, route choice, and departure time choice in transport demand modelling (M. E. Ben-Akiva & Lerman, 1985; Train, 2009). For instance, in mode choice applications, alternatives might include car, bus, train, bicycle, and walking, with utilities specified as functions of travel time, cost, comfort, and individual characteristics such as age, gender or income. Estimated model parameters reveal the relative importance of different factors in choice decisions and can be used to predict how changes in transport systems (e.g., new services, pricing policies) might alter travel behaviour (Ranjan & Sinha, 2024).

2.2.2.2 Extensions and Advanced Choice Models

While the MNL model provides a tractable foundation, it relies on the independence of irrelevant alternatives (IIA) assumption, which implies that the relative probabilities of choosing any two alternatives are unaffected by the representative of any other alternatives (M. E. Ben-Akiva & Lerman, 1985). This assumption is often violated in transport contexts where alternatives may be correlated or share common attributes (e.g., different bus routes may be more similar to each other than to car travel).

To address these limitations, researchers have developed more flexible choice model structures. The nested logit model allows for correlation among subsets of alternatives by organising them into hierarchical nests (e.g., all public transport modes grouped together) (M. E. Ben-Akiva & Lerman, 1985; Williams, 1977). This relaxes the IIA assumption within nests while maintaining computational tractability. The mixed logit (or random parameters logit) model further generalises the framework by allowing taste parameters to vary across individuals according to specified distributions, enabling representation of unobserved heterogeneity in preferences (Hensher & Greene, 2003; Train, 2009). For example, the value of travel time savings may vary across individuals based on income, trip purpose, or other factors. More recent developments include latent class models for identify distinct segments of the population with different preference structures (Greene & Hensher, 2003), and integrated choice and latent variable models for incorporating psychological constructs such as attitudes and perceptions into choice frameworks (M. Ben-Akiva et al., 2002). These advances enable richer behavioural representation but come with increased data requirements and estimation complexity.

2.2.2.3 Joint and Sequential Choice Modelling

Recognising that travel decisions are interdependent, researchers have developed models that represent multiple choices jointly or sequentially (Kitamura & Kermanshah, 1984). Joint models simultaneously estimate choices (Bhat & Guo, 2007) such as destination and mode, or activity participation and travel, capturing correlations between these decisions. Sequential models represent decision-making as a process unfolding over time or across a hierarchy of choices, such as first choosing whether to travel, then choosing destination, then mode, then route. These joint and sequential modelling approaches form the foundation of more comprehensive frameworks such as activity-based models, which integrate multiple discrete choice components to represent the full sequence of daily activity and travel decisions (Bowman & Ben-Akiva, 2001a). For instance, an individual might first decide which activities to pursue on a given day, then schedule these activities in time, then choose locations for each activity, then select modes and routes for travel between activities. Each stage can be modelled as a discrete choice problem, with decisions at each stage influencing subsequent choices.

2.2.3 Activity-Based Models

Activity-based models represent a fundamental paradigm shift from traditional trip-based (four-step) models, by explicitly modelling individuals’ daily activity–travel patterns and the resulting travel demand at the individual and household level (Bowman & Ben-Akiva, 2001a; Rasouli & Timmermans, 2014). While four-step models treat trips as independent events and use aggregate zonal data to sequentially predict trip generation, distribution, mode choice, and route assignment, activity-based models recognise that trips are linked within daily activity schedules and that travel decisions are made jointly rather than sequentially.

2.2.3.1 Conceptual Foundations

Activity-based models are grounded in the recognition that travel demand is derived from the need to participate in spatially and temporally distributed activities. Instead of treating isolated trips as the fundamental unit of analysis, these models focus on activities, including their types (work, shopping, leisure, etc.), timing, duration, and locations, and represent travel as the outcome of activity scheduling decisions made under space–time constraints (Axhausen & Gärling, 1992; Jones, 1990). The theoretical foundation draws directly from time geography and activity analysis. Individuals and households are viewed as making joint decisions about which activities to undertake, when and where to undertake them, with whom, and for how long, subject to capability, coupling, and authority constraints in space and time (Hägerstrand, 1970). These activity decisions then imply specific travel needs, including origins, destinations, timings, and associated mode and route choices, that can be modelled to generate predictions of travel demand.

2.2.3.2 Model Structures and Implementation

Activity-based models vary in their specific structures and implementation approaches, but generally consist of several interconnected components. A typical framework includes models of (Bhat & Koppelman, 1999; Pinjari & Bhat, 2011):

- Activity generation: Which activities individuals choose to pursue on a given day, influenced by personal and household characteristics, day of week, and other factors
- Activity scheduling: When activities are scheduled throughout the day, respecting temporal constraints and interdependencies
- Location choice: Where each activity is located, considering spatial distributions of opportunities, accessibility, and preferences
- Mode choice: Which transport mode is used for each trip, based on mode availability, characteristics, and trip attributes

- Departure time choice: Precise timing of trips, balancing desired activity arrival times with travel conditions

These components are often implemented using systems of discrete choice models, with decisions at each stage influencing subsequent choices (McNally, 2000). For example, the chosen location for a work activity constrains feasible locations for subsequent activities through space-time prisms; the chosen mode for one trip in a tour may constrain mode choices for subsequent trips if a vehicle must be returned home.

2.2.3.3 Advantages and Challenges

Activity-based models offer several advantages over traditional trip-based models. They provide more behaviourally sound representations of travel behaviour, explicitly capturing trip chaining, time-of-day trade-offs, and intra-household interactions. They better represent policies affecting activity participation (e.g., telecommuting, flexible work hours) and generate detailed outputs, including complete daily activity–travel schedules rather than just peak-period trip matrices (Bowman & Ben-Akiva, 2001b). However, activity-based models face significant challenges. They require detailed multi-day activity–travel diaries, which are costly and burdensome to collect. They are computationally demanding, simulating complete daily schedules for large populations. Model specification, estimation, and calibration are complex due to numerous interrelated components (Nayak & Pandit, 2023). Finally, validation is difficult, as comprehensive observed data for full schedules are scarce (F. Liu et al., 2014). Despite these challenges, activity-based models represent the state-of-the-art in behaviourally grounded transport demand forecasting and continue to be refined and adopted for transport planning applications.

2.2.4 Traffic Flow Models

While choice models and activity-based models focus on individual travel decisions and their aggregation into travel demand, traffic flow models describe the physical movement and interactions of vehicles on the transport network. These models are essential for understanding how travel demand translates into observable traffic patterns, congestion, and travel times.

2.2.4.1 Macroscopic Traffic Flow Models

Macroscopic traffic flow models treat traffic as a continuous flow, analogous to fluid dynamics, using aggregate variables such as flow q (vehicles per unit time), density k (vehicles per unit length), and mean speed v (Lighthill & Whitham, 1955). The fundamental diagram $q(k)$ shows flow increasing with density up to capacity at critical density k_c, then decreasing as congestion worsens. The Lighthill-Whitham-Richards (LWR) model provides the theoretical foundation for macroscopic traffic flow modelling, representing traffic dynamics using partial differential equations analogous to conservation laws in fluid dynamics (Richards, 1956a). This model can capture the formation and propagation of traffic waves, shockwaves at bottlenecks, and the transition from free flow to congested conditions. Macroscopic models offer computational efficiency for network-level analysis and traffic management (Mohan & Ramadurai, 2013), but aggregate behaviours preclude modelling microscopic phenomena like lane-changing or individual driver responses (Ferrara et al., 2018).

2.2.4.2 Microscopic Traffic Flow Models

Microscopic traffic flow models simulate individual vehicle movements and interactions, providing detailed representation of traffic dynamics at the level of individual drivers and vehicles. The most common microscopic modelling approach is car-following models, which describe how each vehicle n adjusts its speed and position based on the lead vehicle (Brackstone & McDonald, 1999). Classic car-following models include the Gazis-Herman-Rothery (GHR) family, which relate a vehicle's acceleration a_n to the relative speed Δv_n and spacing Δx_n with the lead vehicle (Gazis et al., 1961). More recent models incorporate additional behavioural factors such as driver reaction time T, desired speed v_0 and safe spacing x. The Intelligent Driver Model (IDM) is a widely used contemporary car-following model that produces realistic acceleration and deceleration behaviours (Treiber et al., 2000). Microscopic models also include lane-changing models, which represent drivers' decisions to change lanes based on necessity (e.g., to follow a route) or desirability (e.g., to overtake slower vehicles) (Gipps, 1986). Combined car-following and lane-changing models enable detailed simulation of traffic flow in multi-lane facilities. Microscopic traffic flow simulator such as VISSIM (Fellendorf & Vortisch, 2010), AIMSUN (Barceló & Casas, 2005; Casas et al., 2010), and SUMO (Krajzewicz et al., 2002) implement these models to simulate traffic flow in detailed network representations. These tools are used for detailed analysis of specific facilities, evaluation of traffic management strategies, and study of phenomena requiring individual-vehicle resolution.

However, microscopic models are computationally demanding and require extensive calibration of behavioural parameters (Balakrishna et al., 2007).

2.2.4.3 Mesoscopic and Hybrid Traffic Flow Models

Mesoscopic models occupy a middle ground between macroscopic and microscopic approaches. They model individual vehicles but at an aggregate level, usually employing speed–density relationships and queuing theory. Examples include kinetic theory-based models, such as the Prigogine–Herman model (Nelson & Sopasakis, 1998) and gas-kinetic-based traffic models (Treiber et al., 1999). These models achieve computational efficiency and easier calibration similar to macroscopic models while capturing more behavioural details than pure continuum approaches (Burghout et al., 2005). Hybrid models combine different levels of details in different parts of the network to balance accuracy and efficiency. For example, a hybrid model may employ high-fidelity microscopic simulation for specific facilities of interest, such as complex intersections or bottlenecks, while using mesoscopic simulation for the large surrounding area to reduce data collection effort and computational requirements.

2.2.5 Challenges and Emerging Directions

Despite decades of development, transport demand modelling continues to face challenges. Behavioural representation remains simplified in many conventional and even advanced discrete choice–based models: utility functions are typically static and assume stable preferences and fully rational decision-making, whereas real behaviour involves habit formation, learning, social influence and bounded rationality (Ortúzar & Willumsen, 2011b). Transferability across contexts is limited: models calibrated in one city, population, or time period often perform poorly elsewhere without substantial recalibration or re-specification. Data requirements are substantial: comprehensive models require detailed household and travel surveys, rich network representations, and often additional data sources such as traffic counts or smart card records for calibration and validation (Miller, 2023).

Emerging directions seek to address these challenges through several approaches. Big or new forms of data sources, including GPS traces, mobile phone data (Calabrese et al., 2011), smart card transactions (Zhao et al., 2018) and social media data (Rashidi et al., 2017), offer new opportunities for observing travel behaviour at unprecedented scale and temporal granularity, potentially reducing reliance on expensive traditional surveys (Anda et al., 2017). However, these data sources are often subject to various forms of bias, reflecting selective user groups, incomplete spatial or temporal coverage, and platform-specific user behaviour, which may limit their reliability and generalisability. Machine learning and deep learning techniques are being explored for data-driven demand prediction, potentially complementing or partially replacing traditional model structures in some applications, though concerns remain about interpretability and policy sensitivity (Koushik et al., 2020). Agent-based models provide flexible frameworks for representing heterogeneous individuals, social interactions and learning processes, but they face persistent challenges in calibration, validation and computational scalability (Bastarianto et al., 2023).

The COVID-19 pandemic has also highlighted the need for models that can represent rapid behavioural changes, disruptions to established patterns, and deep uncertainty in future demand. During the pandemic time, public transport ridership declined substantially in the major cities as travel was largely restricted to essential activities. In response to this sharp reduction in demand, transport operators implemented short-term operational adjustments, including reducing service frequencies, suspending night-time services, and temporarily closing selected stations (Gkiotsalitis & Cats, 2021). Furthermore, even where services continued to operate, public transportation demand remained suppressed due to widespread concerns about infection risk. The pandemic also led to more structural changes in work and lifestyle patterns, including the widespread adoption of remote and hybrid working, increased reliance on online shopping, and more flexible daily schedules. These shifts have altered peak travel demand, reduced commuting frequency, and increased variability in travel behaviour. These changes in both service provision and travel behaviour introduced non-stationarity, which traditional models calibrated solely on pre-pandemic historical data are unable to adequately capture, thereby motivating interest in more adaptive and flexible modelling approaches.

2.3 Conceptual Frameworks for Urban Traffic Analysis

The previous sections established that travel emerges from individuals' needs to participate activities distributed across space and reviewed modelling frameworks that are commonly used to model individuals’ travel behaviour and simulate traffic flow patterns. However, observed traffic patterns cannot be fully explained by behavioural and traffic flow models alone. Traffic flows are embedded within a broader urban context and are shaped by factors such as urban built environment, socio-economic characteristics, and the spatial distribution of opportunities. Building on this background, this section introduces key conceptual frameworks from the transport literature that provide theoretical foundation adopted in this thesis.

2.3.1 Transport and Urban Built Environment

2.3.1.1 Theoretical Foundations

Early theoretical work by scholars such as Hansen (1959) established that accessibility, understood as the ease of reaching different activities (Dalvi & Martin, 1976), shapes land use patterns, while land use distributions in turn generate travel demand. This bidirectional relationship creates a feedback cycle: transport infrastructure shapes accessibility, which influences where people choose to live and work, thereby structuring the spatial distribution of activities and the resulting travel demand, potentially prompting further infrastructure investment and land-use change (Wegener & Fuerst, 2004).

Cervero & Kockelman (1997) formalised the "3Ds" framework for understanding how built environment characteristics influence travel behaviour: Density (concentration of activities and people), Diversity (mix of land uses), and Design (street network characteristics, pedestrian infrastructure). This framework was subsequently expanded to include Destination accessibility (ease of access to trip attractions) and Distance to transit (proximity to the nearest transit stop) (Ewing & Cervero, 2010). Research employing these frameworks has consistently demonstrated that built environment characteristics influence mode choice, trip frequencies, and vehicle miles travelled, with denser, more diverse, and better-designed areas generally associated with less car dependence and more walking and public transport use (Stevens, 2017; van Wee, 2002).

Van Wee (2002) established a comprehensive conceptual framework for understanding the bidirectional relationship between land use and transport. This framework emphasises the critical importance of distinguishing between different spatial scales (neighbourhood, city, region) and temporal perspectives, which separate short-term behavioural responses from long-term structural changes like residential and firm relocation. Building on this, Geurs and van Wee (2004) identify accessibility as the primary feedback mechanism that links land-use patterns, travel behaviour, and the transport system. Their work highlights the normative dimensions of planning, arguing that policy interventions must be evaluated through a broad range of indicators beyond simple transport impacts. This includes assessing both economic efficiency (such as consumer surplus and user benefits) and social equity (the distributional impacts across different social groups), as well as the environmental robustness of the system.

2.3.1.2 Research Gaps

While the built environment-transport literature has generated substantial insights, several critical limitations warrant attention. First, the predominant focus has been on how built environment characteristics influence individual travel behaviour (Ewing & Cervero, 2010), such as mode choice, trip generation and distances travelled, rather than on explicit, model-based relationships with aggregate traffic flow patterns. Much of this literature assumes behavioural changes will impact traffic volumes; however, this relationship is heavily mediated by induced demand and network design effects, such as street connectivity, which are not always straightforward in their systemic impact.

Second, contemporary research continues to focus predominantly on residential neighbourhood effects, analysing how the built environment around people’s homes affects individual travel behaviour and how residential self-selection shapes these relationships (De Vos et al., 2018; van Wee et al., 2019). By contrast, fewer studies investigate how built environment characteristics across the wider urban system, including employment centres, commercial districts and major transport corridors, shape the spatial distribution of traffic flows at the network level, leaving a gap in our understanding of how overall urban structure generates spatially differentiated traffic patterns, despite emerging work on built environment and congestion or spatial configuration and aggregated flows (Ding et al., 2025).

Third, empirical research has predominantly relied on traditional built environment measures derived from census data, land use classifications and network analysis. While informative, such indicators may miss important environmental qualities that influence travel, such as streetscape aesthetics, perceived safety or the visible presence of greenery and amenities (Ewing & Cervero, 2010). Emerging data sources like Street View imagery make it possible to capture these qualities at scale, but their systematic integration into transport and mobility research is still relatively limited (Biljecki & Ito, 2021).

This thesis draws on a built environment perspective to analyse relationships between urban context and traffic flow patterns. Rather than focusing solely on how the built environment shapes individual behaviour, the research investigates how traffic flows vary with built environment characteristics through multiple indicators: traditional land-use attributes (residential, commercial and industrial distributions), Points of Interest data capturing fine-grained activity locations, and Google Street View derived attributes describing greenery, building characteristics and infrastructure. This perspective recognises that traffic patterns emerge not only from residents' travel choices but also from the broader urban structure, including where activities cluster, how neighbourhoods differ in composition and amenities, and how these factors interact spatially.

2.3.2 Accessibility and Spatial Equity

2.3.2.1 Theoretical Foundations

Accessibility has emerged as a foundational concept in transport geography and planning, commonly defined as the ease with which people can reach spatially distributed opportunities, services and social connections (El-Geneidy & Levinson, 2006; Geurs & van Wee, 2004). Unlike mobility, which focuses on movement itself, accessibility concerns people's ability to participate in valued activities at different locations, emphasising that the ultimate goal is access rather than movement per se. Geurs and van Wee (2004) distinguish four components of accessibility: the land-use component capturing the amount, quality and spatial distribution of opportunities; the transport component describing the performance and generalised costs of transport systems; the temporal component reflecting the availability of opportunities and time constraints; and the individual component capturing needs, abilities and resources. This multidimensional framework highlights that accessibility emerges from interactions between urban structure, transport provision, activity schedules and population characteristics rather than from any single element alone.

Recent work by Pereira and colleagues has advanced accessibility research by developing more sophisticated, disaggregated measures and placing equity at the centre of accessibility analysis (Pereira et al., 2019). Using large-scale accessibility indicators, Pereira et al. (2019) show that accessibility is highly uneven across urban space and social groups, with disadvantaged populations often facing compounded barriers: they are more likely to live in areas with poorer transport provision, further from jobs and key services, and to have fewer resources such as time, money and private vehicles to overcome these deficits (Pereira et al., 2017). These patterns imply that accessibility inequalities can reinforce broader social inequalities by constraining the life opportunities and activity choices of disadvantaged groups (Lucas, 2012; Pereira, 2018).

A large body of research documents persistent accessibility inequalities along multiple social dimensions. Studies by Lucas (2012) and others on transport-related social exclusion show that low-income populations, racial and ethnic minorities, women, older adults, young people and people with disabilities often face systematic constraints in reaching key opportunities, reflecting intersecting forms of disadvantage. Complementary quantitative work by Pereira and colleagues further demonstrates that such inequalities are not only social but also spatial, with peripheral, low-income and minority-concentrated neighbourhoods typically exhibiting the poorest levels of accessibility to employment and essential services (Pereira et al., 2019; Pereira & Karner, 2021).

2.3.2.2 Research Gaps

While accessibility frameworks have generated valuable insights, several critical considerations merit attention. First, most accessibility studies analyse people's access to opportunities by quantifying how easily residents of different areas can reach jobs, services or amenities, typically through potential accessibility indicators (Geurs & van Wee, 2004). It is less common to use accessibility concepts to interpret traffic flow patterns themselves. However, traffic flows can be seen as spatial manifestations of accessibility: high traffic volumes on particular road links or in certain areas may reflect locations that are highly accessible and therefore attract many trips, but they may also indicate accessibility deficits if people are forced to travel longer distances because local opportunities are scarce or difficult to reach.

Second, accessibility metrics typically focus on potential access, describing what destinations could be reached in principle given transport and land-use configurations, rather than revealed access based on where people actually travel. The gap between potential and revealed accessibility reflects individual preferences, resources and constraints, as recent work comparing potential and realised travel times or perceived accessibility with observed behaviour has shown (Gligorić et al., 2023; Z. Liu et al., 2025). From this perspective, traffic flows can be interpreted as revealed patterns of access: they provide information about where people actually travel, providing a complementary perspective on accessibility to that provided by potential-based indicators.

Third, the relationship between accessibility and traffic flow is complex and bidirectional. Improved accessibility can generate additional traffic by attracting more travellers and trips, but it can also reduce traffic growth by enabling shorter trips, supporting non-car modes and bringing activities closer to where people live (Mehdizadeh & Kroesen, 2025). Disentangling these mechanisms requires careful attention to spatial scale, trip purposes and mode choices, and to how changes in accessibility at one location affect travel patterns across the wider network.

This thesis employs accessibility and equity perspectives to interpret spatial variations in traffic flow patterns rather than to compute accessibility indices directly. Instead of deriving formal accessibility metrics, the analysis explores how traffic flows vary with urban characteristics that correspond to the main components of accessibility: the spatial distribution of opportunities (captured through points of interest and land-use data), transport infrastructure (road characteristics) and population composition (socio-demographic indicators). Patterns whereby areas with particular socio-demographic profiles exhibit systematically different traffic intensities can be interpreted through an accessibility–equity perspective: they may signal underlying inequalities in accessibility, with some groups living in areas where high transport accessibility is achieved primarily through private car use, while others live in areas with poorer local accessibility and more limited financial and time resources, making them heavily dependent on public transport.

2.4 Influential Factors of Urban Traffic Flow

Having established the conceptual frameworks that guide this research, this section synthesises empirical literature on the specific factors that influence urban traffic flow patterns. It reviews what is known about which factors actually shape observed traffic flows and how these relationships manifest empirically. Based on their characteristics and patterns of influence, three types of influential factors are presented: (1) spatial factors, (2) temporal factors, and (3) other relevant factors.

2.4.1 Spatial Factors

Before exploring the methods that is applied in traffic flow analysis, it is worth identifying first what the influential factors of urban traffic flows are and how they shape the spatial variability of traffic patterns. Urban traffic flow is not only a function of transport infrastructure (W. Yue et al., 2022), but also a reflection of broader socio-economic (Caceres et al., 2018; Chakma, 2018) and environmental characteristics of the urban fabric (Y. Pan, Chen, et al., 2020). A comprehensive understanding of these factors is essential for effective modelling, analysis, and policy design (Zambrano-Martinez et al., 2018).

The spatial influential factors of urban traffic flows can be broadly grouped into five categories: road characteristics, socio-demographics, land use, nearby points of interest (POIs), and urban form extracted from Google Street View imagery. Each of these categories captures different aspects of the built and social environment, and their integration provides a comprehensive understanding of urban traffic dynamics.

2.4.1.1 Road Characteristics

Road characteristics fundamentally shape urban traffic flow patterns through their influence on capacity, connectivity, and movement efficiency. The physical attributes of roads create the structural framework within which traffic flows organise and distribute across urban space, including hierarchical classification and geometric dimensions (L. Chen et al., 2022; W. Chen et al., 2024; Q. Huang et al., 2023; K. Li et al., 2024; Pun et al., 2019; Vikram et al., 2022; S. Wang et al., 2018). Road hierarchy plays an important role in determining traffic distribution. Major roads, defined as roads that provide principal and large-scale transport links within or between cities, carry significantly high daily average traffic flows (Y. Li et al., 2024). The geometric characteristics of roads further influence their traffic-carrying capacity. Road length demonstrates a positive relationship with traffic flows (Gupta et al., 2025), as longer segments typically indicate arterial routes supporting continuous through-movement rather than short local-access streets. Similarly, road width exhibits strong associations with traffic volumes. Wider roads accommodate more traffic flow through increased lane capacity (Srivastava & Kumar, 2023), while narrow lanes, often located on branch roads or in low-traffic areas, naturally constrain traffic flows (B. Han et al., 2023). However, the traffic flow on a road is determined not only by its physical characteristics and hierarchical structure, but also by its location within the broader urban environment. Understanding how road characteristics interact with surrounding land use, socio-demographic factors, and other built environment is essential for comprehensively explaining traffic flow distributions across urban areas.

2.4.1.2 Socio-demographics

Socio-demographic characteristics represent another key dimension in explaining variations in urban traffic flow, reflecting the ways in which population composition and household structures shape travel demand and behaviours (Metz, 2012). Variables such as population density, age and gender distributions, level of education, income level, and the presence of children all influence the volume of travel generated from and attracted to different urban areas (Hafiz Aditya et al., 2022; Haseeb & Mitra, 2024; Nnadiri Geoffrey

Udoka et al., 2020; Shirgaokar, 2014). Population density and economic activity create the foundational conditions for traffic generation. Regions with higher population densities and high economic activity typically exhibit higher traffic flows. These areas are typically more attractive due to the employment and financial opportunities they offer, which in turn generate larger volumes of commuting and local travel (Nnadiri Geoffrey Udoka et al., 2020). Income emerges as one of the strongest demographic predictors of vehicle-related travel behaviour and associated traffic generation. Higher income levels contribute positively to traffic flows by increasing rates of car ownership, as vehicles become affordable and enable more discretionary travel, which in turn increases the frequency of car use (Klinger & Lanzendorf, 2016; Nnadiri et al., 2021). Demographic composition further influences travel patterns across urban space. For instance, areas with higher proportions of young and white residents tend to exhibit higher traffic flows (Y. Li et al., 2024). Age structure influences traffic flow through lifecycle effects. Young families generate high numbers of car trips, driven by complex activity schedules involving work, childcare, shopping, and children's activities. Meanwhile, car usage of seniors has increased over time (McCarthy et al., 2025), reflecting growing dependence on private vehicles within ageing populations (K. B. Newbold et al., 2005). The presence of children and household structure also influence traffic generation, with more children generally associated with increased car usage (Klinger & Lanzendorf, 2016). These demographic-traffic relationships are not only statistical associations but reflect the ways population characteristics interact with urban structure, accessibility, and transport provision to shape travel possibilities and constraints. Therefore, comprehensively understanding traffic flows requires exploring how demographic composition interacts with built environment, land use, and transport infrastructure characteristics to generate the observed urban traffic flow.

2.4.1.3 Land Use

Land use pattern is the spatial distribution of different human activities and urban functions across urban landscape, which is another fundamental determinant of traffic flow. Land use is defined as the human function of a given area (Pauleit et al., 2005), including the different ways people occupy, develop, and interact with the land surface (Q. Liu et al., 2021). As urban development intensifies and human activities reshape urban land in both physical form and socioeconomic purpose (J. Yin et al., 2021), the relationship between land use and urban traffic flow reflects how the spatial distribution of urban activities generates transportation demand (Jadaan & Nicholson, 1992). Different land use types generate distinctly different traffic patterns through their functional roles in the urban system. (Y. Li et al., 2024; T. Zhang et al., 2017; Y. Zhang & Raubal, 2022). Commercial land use exhibits positive relationship with higher traffic flows due to its function as a centre for employment and consumer activity (Izanloo et al., 2017). Commercial areas attract workers commuting to jobs and customers traveling to shops, creating concentrated traffic flows throughout business hours. In contrast, some land use types are associated with considerably lower traffic intensities. Natural and green spaces typically exhibit lower traffic flows (Y. Li et al., 2024), as these areas function primarily as amenities rather than activity hubs. Industrial areas tend to generate relatively low traffic flows compared to commercial areas, despite their employment function (Y. Zhang & Raubal, 2022). This pattern reflects their peripheral locations and limited attraction of traffic outside of working hours. In addition to the effects of individual land use types, the mixing configuration of different uses substantial influence traffic patterns. In high-density and mixed-use neighbourhoods, residential, commercial, and service activities are closely integrated. These areas are associated with fewer motorised vehicle trips, shorter travel distances, and less travel times compared to single-use, low-density areas. (Abbiasov et al., 2024; Van Acker et al., 2007). This pattern emerges because land use mixing enables people to access multiple destinations within walkable or short-distance ranges, reducing both the need for vehicle travel and the distances travelled when vehicles are used. Therefore, mixed-use development can encourage active travel and contribute to lower carbon emissions (Mumford et al., 2011; Zagow, 2020). The spatial distribution of land uses creates the fundamental structure of travel demand within cities, as the location of activities determines where people need to go, how far they must travel, and which modes are viable for reaching their destinations. Therefore, understanding traffic flow patterns requires exploring not only which land uses are present but also how their spatial distribution and development intensity enable or constrain different travel behaviours.

2.4.1.4 Nearby Points of Interest (POIs)

While traditional land use classifications provide broad characterisations of urban functions, Points of Interest (POI) data offer fine-grained, location-specific information about the actual destinations and activities that generate travel demand. POI data provide digital representations of specific places in the real world that are of interest to particular population groups (K. Sun et al., 2023). Although some POIs are located in natural areas (Hewitt et al., 2021), the majority are clustered in densely urbanised regions where they play important roles in supporting various human activities (S. Gao et al., 2017; Psyllidis et al., 2022). As digital proxies for functional urban locations, POIs are typically represented as geometric point entities with precise spatial coordinates (Y. Li et al., 2024; Psyllidis et al., 2022). In urban studies, they are widely used to understand human mobility patterns, support city planning, and develop smart city infrastructures (Y. Cheng et al., 2024; K. Sun et al., 2023). Research has developed detailed POI classification schemes, including transport facilities, educational and medical institutions, food and beverage services, shopping and retail, residential communities, entertainment and leisure venues, and public infrastructure (Y. Li et al., 2024; Nian et al., 2020; K. Wang et al., 2023; X. Wu et al., 2025; Z. Xu et al., 2019). Researchers find that traffic flows are influenced by the distribution and types of nearby POIs (X. Huang et al., 2023; K. Wang et al., 2023; X. Wu et al., 2025). Areas with high densities of consumption-related POIs (e.g., shopping centres, restaurants) exhibit higher traffic flows (Nian et al., 2020), as these facilities attract visitors from throughout the urban area and generate activity over long hours. Transport infrastructure POIs such as bus stations often corresponds to increased commuting flows (S. Wang et al., 2018). Besides, POIs illuminate the temporal dimensions of traffic variability.. For instance, working districts experience obvious morning and evening peaks, while entertainment areas generate traffic flows concentrated in the evening or during weekends (Q. Huang et al., 2023). The POI composition of an area shapes not only the volume of traffic but also when that traffic occurs. Therefore, understanding how POI densities, types, and spatial distributions relate to traffic patterns provides insight into the fine-grained urban characteristics that generate and shape traffic flows, complementing the broader perspectives offered by land use categories and socio-demographic indicators.

2.4.1.5 Urban Form from Google Street View Imagery

While traditional urban data sources provide top-down, administrative characterisations of the built environment, such as land use types and census statistics, Google Street View (GSV) imagery offers a fundamentally different perspective. It provides a street-level, human-scale view of urban environments as actually experienced by travellers. GSV is a widely used source of publicly available Street View Images (SVI) that provide panoramic, street-level photographs of urban environments (Anguelov et al., 2010; Biljecki & Ito, 2021; X. Li et al., 2015, 2017; Y. Li et al., 2022). These images are typically captured by a mobile mapping system mounted on vehicles (Hoelzl & and Marie, 2014), offering an omnidirectional and “eye-level” perspective of city streets (Cinnamon & Jahiu, 2021; S.-N. Kim & Lee, 2022). One particular strength of GSV for transport research is its ability to capture human and vehicular activity that may be underrepresented in traditional data resources (Goel et al., 2018). Street-level imagery reveals the actual on-the-ground conditions facing travellers, such as the presence or absence of sidewalks, the density of street vegetation and the character of building frontages. These environmental qualities influence travel experiences and mode choices in ways that traditional datasets cannot fully capture. Therefore, GSV provides a complementary data source for understanding and modelling urban traffic flows and mobility patterns. Researchers have applied GSV imagery across diverse transport-related applications. Studies have used GSV to estimate pedestrian and vehicle flows by counting visible travellers and vehicles in images (Ezekiel Rito et al., 2021). Other research has focused on characterising street-level built environment features, including assessing sidewalk presence, quantifying visible greenery, and evaluating road quality (Martell et al., 2024; Charreire et al., 2014; J.-I. Kim et al., 2023). By identifying and classifying different types of road users and vehicles in GSV images, researchers are able to estimate city-level travel behaviours, including rates of walking, cycling, and car commuting (Goel et al., 2018). The application of GSV imagery in traffic flow research represents an integration of emerging data sources with traditional transport analysis. Computer vision techniques are applied to extract quantitative features of environmental features from SVI. Understanding how these street-level environmental qualities relate to traffic patterns provides insight into the full range of urban characteristics that influence mobility, extending beyond functional attributes like land use to include experiential qualities of urban space that influence how people choose to move through cities.

2.4.2 Temporal Factors

In addition to spatial variability, urban traffic flows also exhibit significant temporal dynamics (Treiber & Kesting, 2013), shaped by a range of time-sensitive and situational factors. These temporal factors influence fluctuations in urban traffic flow throughout the day, week, or year (Batterman, 2015; D. Ma et al., 2021; Stathopoulos & Karlaftis, 2001). Understanding these variations is important for capturing both the short-term and long-term patterns in urban human mobility (Habtemichael & Cetin, 2016; G. Lai et al., 2018; Moosavi et al., 2019). The temporal influential factors of urban traffic flows can be broadly classified into four main categories: time of day, day of the week, holidays and seasonal variations, and special events. Each of these elements contributes uniquely to the temporal dynamics of traffic flow and, when incorporated into traffic modelling, can significantly improve the reliability of forecasting systems (P. Lin et al., 2022; W. Zhang et al., 2021).

2.4.2.1 Time of Day

The hourly rhythm of traffic flow throughout the day represents one of the most fundamental and visually apparent patterns in urban mobility data. Human activity exhibits strong daily periodicity (Y. Zhao et al., 2023), with distinct fluctuations corresponding to routine daily activities such as commuting, schooling, and leisure (Gupta et al., 2025; S. Pan et al., 2024; H. Wang et al., 2021). These fluctuations result in significant temporal shifts in mobility hotspots and the spatial redistribution of traffic demand throughout the day (Sadeghian & Mojarrad, 2025). The most typically feature of weekday traffic patterns is their distinctive bimodal character on weekdays, with two clear peaks: one in the morning and one in the evening (M. Zhou et al., 2016).

The morning peak, usually observed between 05:00 and 10:00, corresponds to daily commutes from home to workplaces (Olayode et al., 2025; Sadeghian & Mojarrad, 2025; Sanik et al., 2025; H. Xiong et al., 2021; Y. Zhao et al., 2023). Analysis of hourly traffic data shows trip generation rates and flow volumes reaching their highest levels during these morning hours, with specific modes like taxi trips peaking around 9:00 as work day commences (H. Xiong et al., 2021). The evening peak, often occurring between 17:30 and 18:30, reflects the end of standard work hours and the return journey from employment centers to residential areas (Olayode et al., 2025; Sadeghian & Mojarrad, 2025; Sanik et al., 2025; H. Xiong et al., 2021; Y. Zhao et al., 2023). Evening peaks often exhibit slightly longer duration and more spatial dispersion than morning peaks, reflecting the greater diversity of post-work activities.

Between these two peaks, mid-day periods, typically between 10:00 and 15:00, also remain relatively high traffic levels compared to overnight hours, though substantially lower than peak traffic volumes (Olayode et al., 2025). This mid-day activity reflects commercial operations such as business-related travel. Conversely, overnight periods, particularly the hours between midnight and early morning, exhibit the lowest traffic volumes of the daily cycle. However, even during these typically quiet hours, certain urban locations remain active. Hotspots often emerge in city centres as entertainment districts generate visitor traffic during late-night hours (Sadeghian & Mojarrad, 2025). This spatial variation in temporal patterns suggests that human mobility is not static but exhibits dynamic interactions among different urban functional areas at different times of day (Y. Zhao et al., 2023). These dynamic patterns also highlight the importance of adopting time-sensitive approaches to urban mobility management (Sadeghian & Mojarrad, 2025).

Recent developments in traffic prediction modelling have explicitly incorporated temporal features representing hour of day, with deep learning incorporating peak-hour embedding to capture the differences between peak and off-peak periods (Wei et al., 2024). By modelling these temporal dependencies, traffic forecasts achieve improved robustness and accuracy (X. He et al., 2025). Therefore, understanding time-of-day patterns is essential both for interpreting observed traffic variations and for developing models that can anticipate how traffic will evolve throughout the daily cycle.

2.4.2.2 Day of the Week

Traffic flows also vary considerably across the days of the week, with clear behavioural distinctions between weekdays and weekends (F. Xia et al., 2018; X. Yang et al., 2024). This weekly periodicity arises from social organisation of work, education and leisure time in most contemporary urban societies. Standard working days typically cover from Monday to Friday, characterised by routine commuting for work, education, and structured activities (H. Shi et al., 2025). Saturday and Sunday function as day of rest, recreation and discretionary activity when work-related travel are reduced (H. Xiong et al., 2021; Yoongsomporn et al., 2025; J. Zhang et al., 2025). Weekday traffic patterns exhibit the strong temporal regularity described in the previous section. Two distinct peaks in activity are commonly observed at 09:00 and 18:00, corresponding to work start times and homebound commutes. These temporal structures often disappear on weekends, where a single and broader mid-day peak around 13:00 is more typical (Sparks et al., 2022; H. Xiong et al., 2021), with higher concentration of recreational and shopping-related movement (H. Shi et al., 2025; F. Xia et al., 2018).

Weekend travel also demonstrates greater variability and spatial distribution. People on weekdays are more likely to travel with short distance as people travel between fixed, regular locations using established routes. Weekend travellers tend to make longer-distance trips, as people travel beyond their immediate neighbourhoods to reach recreational destinations, visit friends and family in other areas, or explore commercial and entertainment options throughout the metropolitan area (F. Xia et al., 2018; X. Yang et al., 2024). However, mixed-use development and increased availability of commercial facilities can reduce the necessity for long-distance travel, enabling residents to fulfil weekend needs close to home (McCormack et al., 2001; X. Yang et al., 2024). Therefore, the differences between weekday and weekend patterns have important implications for traffic analysis and prediction. Incorporating day-of-week indicators or separate model structures for weekdays versus weekends helps capture of these distinct behavioural regimes (Bouzaghrane et al., 2024; K. Zhang et al., 2023). Embedding these weekday-weekend characteristics into models has been shown to improve prediction accuracy by recognising the periodicity and behavioural regularities in weekly mobility cycles (X. Yan et al., 2024; W. Zeng et al., 2023). Understanding day-of-week variations is thus essential for both interpreting observed traffic patterns and for developing models that can anticipate how traffic will vary not just within days but across the weekly cycle.

2.4.2.3 Holidays and Seasonal Variations

Holidays and seasonal changes introduce complex temporal heterogeneity into urban traffic flow, leading to both predictable and irregular mobility behaviours (T. Lin & Lin, 2025). These disruptions differ significantly from routine patterns (Q. Chen et al., 2024; Ul Abideen et al., 2024; H. Zhu et al., 2019), often resulting in changed peak periods and spatial variation of traffic flows (M. Gao et al., 2025; T. Lin & Lin, 2025). Business districts that dominate weekday traffic flows may become quiet on holidays, while recreational areas, tourist attractions, and transportation hubs experience elevated activity.

During holidays, traffic demand demonstrates a notable shift from rigid, routine commuting to more elastic and leisure-driven travel (Y. Han et al., 2020; B. Wang et al., 2015). At the intercity level, holiday periods often trigger explosive growth in travel demand (B. Song et al., 2022), as urban residents travel to other cities for vacation, family visits, or tourism. During these periods, traffic flow tends to exhibit weaker regular temporal patterns, showing only slight peaks at the beginning and end of holidays (L. Gao, 2025). These peaks indicate a strong “backflow” effect as large number of people simultaneously depart from and return to urban centres (W. Yu et al., 2024). In contrast, intra-city travel tends to decrease during holidays due to reduced commuter activity and population outflows, especially in business and residential areas (T. Lin & Lin, 2025; W. Yu et al., 2024). But tourist attractions and shopping centres may still experience localised increase in traffic flows (Y. Han et al., 2020), as they attract both remaining residents and visitors from outside the city. Therefore, the effect of holidays on urban traffic varies spatially, with some areas quieter and others busier than usual, creating a reconfigured geography of activity during holiday periods.

Seasonal variation provides the broader temporal context within which holidays occur and create additional, longer-period fluctuations in travel patterns. For example, travel behaviours are typically more varied during winter and summer (Holmes et al., 2021), due to longer school breaks and more favourable weather conditions. As work and school schedules shift with the seasons, commuting behaviours are correspondingly adjusted (Q. Chen et al., 2024), impacting both travel timing and frequency. These seasonal shifts interact with and intensify the effect of holidays. A public holiday occurring during a school vacation period may show different travel patterns than the same holiday during a school term, because the presence or absence of school schedules affects household constraints and opportunities. The temporal complexity introduced by holidays and seasonal variations creates significant challenges for traffic analysis and prediction. Incorporating explicit holiday indicators and seasonal adjustment factors into forecasting frameworks allows models to adapt to these atypical patterns, substantially improving accuracy during these challenging periods (J. Li et al., 2025; J.-D. Wang & Oktomy, 2024; L. Gao, 2025).

2.4.2.4 Special Events

Beyond the periodic cycles of daily, weekly and seasonal patterns, urban traffic is also affected by special events, such as concerts, sports games, and New Year celebrations (Liang et al., 2024; Marques-Neto et al., 2018; H. Yang et al., 2023; Raskar & Nema, 2022; J. Zhang et al., 2018). These events serve important urban functions, contributing to cultural life and economic vibrancy by bringing large numbers of people together (Liang et al., 2024). However, although special events attract concentrated crowds, they also create substantial transportation challenges (B. Guo et al., 2023; Y. Song et al., 2024). Large-scale events can draw tens of thousands of attendees to single venues within narrow time windows (Marques-Neto et al., 2018), overwhelming the normal capacity of surrounding street networks and transit systems (S. Xu et al., 2018; G. Xue et al., 2022). Unlike routine travel patterns, mobility during special events often shows dramatically different patterns. Pre-event periods, typically in the hour or two before an event begins, see substantial traffic inflows as attendees converge on venues. Post-event periods experience equally dramatic outflows, often even more concentrated than inflows, as thousands of attendees simultaneously exit venues when events conclude and attempt to leave the area at once (Y. Song et al., 2024; H. Yang et al., 2023). This double-surge pattern is characteristic of event impacts and readily distinguishable in traffic data from the patterns of routine travel (Z. Huang et al., 2018).

To effectively manage such traffic disruptions, an increase number of research focuses on capturing the spatio-temporal characteristics of events (Marques-Neto et al., 2018; H. Yang et al., 2023). Researchers have employed Mobile phone data and GPS traces to detect event signatures in mobility data (Z. Huang et al., 2018), inferring event start and end times, venue locations and attendee flows from observed movement patterns. By incorporating the extracted event-specific characteristics and historical traffic flow data into models, it helps improve the prediction accuracy on the days of events (Abadi et al., 2015; Fofanah et al., 2025; Y. Song et al., 2024). Besides, recent development in large language models (LLMs) have opened new possibilities for incorporating event information. For example, LLMs can process unstructured textual descriptions of events to extract relevant features about event characteristics, and then integrate this information with historical mobility data to improve the forecasting of travel demand during public events (Liang et al., 2024). By dynamically adjusting traffic predictions based on the unique temporal and social context of each event, these advanced modelling approaches can capture event impacts more accurately than traditional time-series methods (Rodrigues et al., 2019). Therefore, understanding and anticipating special event impacts represents an important dimension of comprehensive traffic analysis, which extends beyond regular temporal patterns to consider episodic disruptions that influence urban mobility.

2.4.3 Other Factors

In addition to spatial and temporal influences, there are other external factors that can cause a substantial impact on urban traffic flow. These factors include government interventions and unforeseen events that disrupt normal traffic conditions. Government policies, such as congestion charging schemes (Andersson & Nässén, 2016; Kaida & Kaida, 2015; Ouali et al., 2021) and emergency public health interventions during the COVID-19 pandemic (de Haas et al., 2020; Hadjidemetriou et al., 2020), have been shown to significantly change traffic patterns by influencing travel demand and mobility behaviour. Besides, unexpected disruptions such as traffic accidents introduce sudden fluctuations in traffic speed and volume (Y. Xu et al., 2018; Z. Yu et al., 2024), causing localised congestion and changing traffic dynamics across the road network. Understanding these other influential factors is essential for enhancing traffic prediction models and ensuring that transport policies and intelligent traffic management systems remain responsive to real-world conditions (Berhanu et al., 2023).

2.4.3.1 Government Policies

Government policies aimed at urban traffic flow represent deliberate efforts to manage mobility through regulatory, economic, or administrative measures. Among the most extensively studied policy interventions are congestion charging schemes. These systems impose fees on vehicle travel into designated zones or on specific roads during particular times. They are designed to reduce vehicle numbers in high-demand areas, encouraging the use of public transport, and reducing carbon emissions (Alrukaibi, 2021). The empirical evidence on congestion charging impacts provides clear documentation of how policy interventions can rapidly reshape traffic patterns. Singapore was the first to implement such an intervention with the Area Licensing Scheme (ALS) in 1975, aimed at reducing traffic in the Central Business District (CBD) (M. Z. F. Li, 2002). The policy led to an immediate 43% reduction in the total number of motor vehicles during the morning peak hours within the Restricted Zone by the fourth week of implementation (Phang & Toh, 2004). Similarly, London introduced the Congestion Charging Scheme (CCS) in 2003 in Central London (Green et al., 2016), covering the city's key government, business, financial, and entertainment districts (Santos, 2005). The scheme led to a 27% decrease in the number of private automobiles within Central London. On average, daily traffic flow within the charge zone is approximately 20% lower than in adjacent areas outside the zone (C. K. Tang & van Ommeren, 2022). Stockholm followed with a cordon-based congestion pricing system in 2006 (Börjesson & Kristoffersson, 2018), which led to a 22% reduction in traffic flow across the cordon during the first month. The decrease was largest during the afternoon peak (−23%) and slightly lower in the morning peak (−18%). This suggests that a large proportion of discretionary trips occur in the afternoon, and departure times from work are more flexible than arrival times in the morning (Eliasson et al., 2009). Overall, the evidence demonstrates that congestion pricing can produce lasting changes in travel behaviour, as commuters adjust their travel modes, routes, or departure times in response to the new economic and temporal constraints.

While congestion charging represents planned and ongoing policy interventions that became embedded features of urban transport systems, the COVID-19 pandemic introduced a fundamentally different type of government intervention. During the pandemic, governments implementing lockdowns, travel restrictions, and social distancing policies (Carteni et al., 2020; Sahraei & Ziaei, 2024; Z. Zhang et al., 2023), leading to an unprecedented disruption in global mobility (Harantová et al., 2022) and dramatic reductions in traffic flow worldwide (Owen et al., 2020). In the United States, traffic flow decreased by 30% to 40% following the implementation of social distancing measures (Mendoza et al., 2020), and declined further to 40% to 65% following the adoption of stay-at-home orders (Du et al., 2021). Italy experienced even more severe reductions, with a 69–88% decrease in traffic flow on working days and a 74–92% drop on non-working days, and hourly reductions reaching as high as 99% during certain periods (Ravina et al., 2021). These numbers represent traffic collapses of a magnitude never before observed in peacetime urban contexts. In the United Kingdom, Oxford saw a 77.5% reduction in daily traffic flow during the first national lockdown, exceeding the national average reduction of 40%. This substantial decline was likely driven by disruptions in the education sector, including reduced attendance at schools, colleges, and universities during term time (A. Singh et al., 2022). In France, the total number of daily trips dropped by 65%, from 57 million to 20 million, particularly affecting work-related and long-distance travel (Pullano et al., 2020). China, where the pandemic first emerged and where some of the earliest and strictest control measures were implemented, recorded a nationwide traffic flow decline of 78.5% during its traffic control stage (X. Jiang et al., 2021). The pandemic experience demonstrated how government policies can essentially override the normal determinants of traffic flow. The spatial-temporal characteristics, demographic and land use patterns that ordinarily shape traffic became temporarily secondary to policy-imposed constraints on urban mobility. This natural experiment provided unprecedented insight into traffic system plasticity and the potential for policy interventions to reshape mobility fundamentally when sufficiently motivated and enforced.

2.4.3.2 Traffic Accidents

Traffic accidents represent a fundamentally different category of external factor compared to government policies. Traffic accidents are unexpected incidents that often cause immediate congestion and long-lasting impacts on network performance (J. Zeng et al., 2019). These accidents typically lead to sudden changes in traffic speed and density, particularly in the upstream direction, where vehicle queues can rapidly form as inflow exceeds the reduced road capacity. When traffic approaches saturation, even minor accidents can generate severe congestion, and once the obstruction is cleared, dissipation of traffic queues may still take an extended period (Lv & Huang, 2017). Empirical evidence shows that as vehicles approach an accident scene, they decelerate gradually and often change lanes, resulting in queue formations and reduced throughput at the incident site. These behaviours reduce throughput even in lanes that are not physically obstructed by the accident itself, amplifying the capacity loss beyond the physical blockage itself.

After vehicles pass the accident location, traffic flow stabilises but often at changed speeds and volumes compared to pre-incident conditions (Xie & Feng, 2013). These spatio-temporal disruptions can also influence adjacent roads, dynamically changing the topology of the road network (Ye et al., 2023). Congestion propagates upstream along the road as queues extend backward from the bottleneck, potentially reaching highway on-ramps, intersections, or adjacent road segments.

Incorporating accident effects into traffic analysis and forecasting presents challenges due to accidents' unpredictable occurrence. Historical accident data can inform probabilistic assessments of accident likelihood at different locations and times, and real-time incident detection systems can identify accidents as they occur, enabling dynamic adjustment of forecasts and management responses. Recent studies have incorporated traffic accident information into traffic prediction models, including the time and location of the accident (Y. Liu et al., 2022). By constructing accident-related adjacency matrices and integrating real-time accident data into traffic flow forecasting frameworks (Ye et al., 2023), researchers have demonstrated improvements in prediction accuracy under incident conditions (An et al., 2019). These advantages highlight the critical role of accounting for accident effects in traffic modelling and management. Therefore, understanding traffic accidents as an external factor affecting flow is essential both for real-time traffic management and for traffic forecasting systems that must maintain accuracy under the full range of conditions including incident-disrupted periods.

2.5 Chapter Summary

This chapter has reviewed the literature that supports the empirical studies of this thesis, structured across four interconnected themes: travel behaviour and mobility constraints, transport demand modelling, conceptual frameworks for urban traffic analysis, and influential factors of urban traffic flow. Across these themes, the review has revealed a set of consistent limitations in existing research. The literature on travel behaviour and mobility constraints demonstrates that urban mobility is influenced by socio-economic characteristics and differentiated constraints, while also highlighting the underrepresentation of disadvantaged groups in conventional transport planning frameworks. The literature on transport demand modelling demonstrates the evolution of increasingly sophisticated approaches to capturing travel behaviour, but also highlights the challenge of addressing dynamic, disruption-driven behavioural changes such as those caused by the COVID-19 pandemic. The conceptual frameworks reviewed provide the theoretical background for the empirical analyses, emphasising that traffic flows must be understood as socially and spatially shaped by the characteristics of urban neighbourhoods and the constraints faced by different population groups. The review of influential factors identifies the wide range of physical, social, and temporal determinants of urban traffic dynamics, emphasising their variation across space and time.

Chapter 3 Analytical Methodology for Urban Traffic Flow

Understanding which factors influence urban traffic flow provides essential empirical knowledge, but translating this knowledge into robust analysis and prediction requires appropriate methodologies. This chapter introduces the methodology used to analyse and predict traffic flow in urban environments. Based on the characteristics of urban traffic flow, two methodological frameworks are presented: (1) regression analysis for quantifying relationships between factors and traffic flow, (2) temporal analysis for modelling and predicting traffic flow patterns over time.

3.1 Regression Analysis

Regression analysis provides the foundational statistical framework for quantifying the relationship between urban influencing factors and traffic flow (Sarstedt & Mooi, 2019; Sykes, 1993). Specifically, it models how a dependent variable varies as a function of one or more independent variables. Over time, a variety of regression models have been developed for different types of influencing factors. These models can be classified according to three key criteria: the number of independent variables (Lewis-Beck & Lewis-Beck, 2015), the type of dependent variable (Chatterjee & Hadi, 2015), and the functional form of the regression relationship (Kendall, 1951). The advantages of regression analysis are twofold. First, it enables the evaluation of whether a statistically significant relationship exists between the independent variables and the dependent variable. Second, it allows for the quantification of the strength of the impact that each independent variable has on the dependent variable (Sarstedt & Mooi, 2019):

3.1.1 Linear Regression Model

Among the various regression models, linear regression model is one of the most commonly used due to its simplicity, interpretability, and effectiveness in quantifying relationships between variables (Roustaei, 2024). As a foundational approach in statistical modelling (X. Su et al., 2012), linear regression assumes a linear relationship (Draper & Smith, 1998; Roustaei, 2024) between a dependent variable, such as traffic flows, and one or more independent variables that may include road characteristics, socio-demographics, and surrounding built environments. In this model, independent variables can be both continuous (e.g., population density, road length) and discrete (e.g., road type, land use category) (WALTER et al., 1987), while the dependent variable remains continuous (e.g., average daily traffic flow) (Hope, 2020). In the context of urban traffic analytics, the linear regression model serves as a starting point for exploring how various urban influencing factors contribute to observed traffic flows across time and space. Since there are more than one independent variables that may influence the urban traffic flows (Pun et al., 2019; S. Wang et al., 2018), a multiple linear regression model can be defined as (Tranmer et al., 2020):

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \tag{2-1}$$

Where

$$\boldsymbol{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \tag{2-2}$$

$$\boldsymbol{X} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{pmatrix} \tag{2-3}$$

$$\boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{pmatrix} \tag{2-4}$$

$$\boldsymbol{\epsilon} = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} \tag{2-5}$$

Where $\boldsymbol{y}$ is a vector of dependent variable average daily traffic flow of each SCOOT sensor, and n is the number of sensors; $\boldsymbol{X}$ is a matrix of various independent variables, include road characteristics, socio-demographics and surrounding built environments affect traffic flows, and m is the number of those influential factors; $\boldsymbol{\beta}$ is a vector of regression parameters to be estimated based on variables and $\boldsymbol{\epsilon}$ presents a vector of unobserved variables, also known as error term for the regression model.

In the research, the ordinary least squares (OLS) method (Montgomery et al., 2021) is used to estimate parameters $\boldsymbol{\beta}$, which minimises the sum of squared errors (SSE) (Acito, 2023; James et al., 2023; Pohlmann & Leitner, 2003) between observed traffic flows and estimated values. The OLS method requires several assumptions, including normality, homoscedasticity and independency of residuals (de Souza & Junqueira, 2005). It can be defined as:

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X})^{-1}\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{y} \tag{2-6}$$

Where $\boldsymbol{X}^{\boldsymbol{T}}$ is the transpose of $\boldsymbol{X}$ and $\boldsymbol{X}^{-\mathbf{1}}$ is the matrix inverse of $\boldsymbol{X}$.

Linear regression models have been widely applied in traffic flow analysis due to their interpretability and effectiveness in capturing linear relationships between influencing factors and traffic flows. Several studies have demonstrated the utility of both simple and multivariate linear regression techniques in urban traffic flow (Pun et al., 2019): log-linear regression models estimate average traffic flow from roadside noise levels, exploiting the proportional relationship between noise levels in decibels and vehicle counts (Venkataraman & Rumpler, 2025); straightforward linear regression predicts daily number of vehicles for basic traffic forecasting applications (Naveed et al., 2024); Multiple Linear Regression Units (MLRU) transform time series forecasting into a regression problem by incorporating traffic flow characteristics from neighbouring series, including seasonality, trend, residuals, and cyclic patterns to enhance prediction robustness (Rajeh et al., 2023); enriched regression frameworks incorporate traffic indicators derived from social media data, such as Twitter, to capture real-time activity patterns(J. He et al., 2013); and multivariate linear regressions combine spatial static attributes with dynamic traffic flow data to achieve high prediction accuracy in short-term traffic prediction (D. Li, 2020). These diverse applications demonstrate the flexibility and utility of linear regression across a wide range of traffic analysis tasks. The model’s transparency, with coefficients that have direct and intuitive interpretations as marginal effects, makes the results readily comprehensible to both researchers and practitioners. In addition, its computational efficiency allows it to be applied to large-scale datasets, while its statistical foundations provide well-developed frameworks for uncertainty quantification and hypothesis testing. For these reasons, linear regression remains a cornerstone method in traffic analysis, serving both as a standalone analytical tool and as a baseline against which more complex methods are evaluated.

3.1.2 Spatial Regression Models

While standard linear regression models assume that relationships between dependent and independent variables remain constant across geographic space, this assumption often does not hold in urban environments where spatial dependence are prevalent (Longley & and Tobón, 2004). The explanation of urban traffic relationships via linear regression is limited in its ability to account for the phenomenon whereby two measurements taken from geographically close locations are often more similar than those from widely separated areas (L. Li et al., 2012; Miller, 2004; Tobler, 1970). For instance, the traffic flows of two adjacent road links are generally more similar than those of roads located further apart or disconnected. This phenomenon, known as spatial dependence, occurs when the value of a variable at one location is influenced by values at nearby locations (Crawford, 2009). Spatial regression models can quantify this interdependence using spatial autocorrelation indices, which measure the degree of similarity among neighbouring observations.

To address these limitations, spatial regression models extend the traditional linear framework by incorporating spatial dependence directly into the analysis. In the context of urban traffic flow, spatial regression models help account for the spatial structure of the road network and the built environment, thereby improving both model accuracy and interpretability. For example, traffic conditions at one location are often influenced by those in adjacent areas through the road network (X. Fu et al., 2022). Ignoring such spatial interdependencies can lead to biased traffic analysis. To measure the spatial dependence of urban traffic flow, spatial regression models incorporate a spatial weight matrix, which is a mathematical representation of the spatial structure of observations (Getis, 2009; Getis & Aldstadt, 2004). This matrix defines how each location (e.g., a traffic sensor or road segment) is connected to or influenced by other locations, typically based on geographical proximity or network connectivity (Ermagun & Levinson, 2018; Getis & Aldstadt, 2004).

After identifying the spatial relationship between traffic flow observations using the spatial weight matrix, the next step is to select an appropriate spatial regression model that effectively captures the identified spatial dependencies. Different models are suited to different forms of spatial dependence. A commonly used global method is the spatial autoregressive model (SAM), also known as the spatial lag model, which assumes that spatial autocorrelation exists within the dependent variable itself. This model includes a spatially lagged dependent variable to account for the influence of neighbouring observations on traffic flow (Griffith, 2009; H. Li et al., 2007). The spatial error model

(SEM) assumes spatial autocorrelation is a result of some unobserved variable(s) that influence traffic flow and is present in the residuals of the model (D.Ward & SkredeGleditsch, 2008). The spatial Durbin model (SDM) is an extension of the SAM that assumes spatial autocorrelation may be present in both the dependent and independent variables (Mur & and Angulo, 2006).

The SAM can be defined as (Ord, 1975):

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \tag{2-7}$$

The SEM can be defined as (Anselin, 1988):

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\mu} \tag{2-8}$$

$$\boldsymbol{\mu} = \lambda \boldsymbol{W}\boldsymbol{\mu} + \boldsymbol{\epsilon} \tag{2-9}$$

The SDM can be defined as (Durbin, 1960):

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\theta} + \boldsymbol{\epsilon} \tag{2-10}$$

Where $\boldsymbol{W}$ is the spatial weight matrix. $\boldsymbol{W\mu}$ represents correlated interaction effects, which capture the influence of similar unobserved urban environmental characteristics across adjacent neighbourhoods, and the influence is captured by the spatial error coefficient λ. $\boldsymbol{Wy}$ refers to endogenous interaction effects, which describe the spatial dependence of traffic flows in neighbouring areas, measured by the spatial lag coefficient ρ. $\boldsymbol{WX}$ is the exogenous interaction effects (L. Lee & Yu, 2016), which reflect the spatial spillover of independent variables across adjacent neighbourhoods. These interactions are captured by the spatial autoregressive coefficient $\boldsymbol{\theta}$, highlighting how urban characteristics in surrounding areas affect local traffic flow.

These spatial regression models have been widely applied in traffic research to explore spatial autocorrelation between urban environment and urban traffic behaviour. One study applies the SDM to analyse the relationship between environmental conditions and travel behaviour, revealing that tourists prefer areas with better air quality while reducing visitation to adjacent areas with poorer conditions (Hwang et al., 2025). Research on walking route choices to schools uses SEM to identify spatial relationships between route choice and individual characteristics such as age, gender, and health (Rybarczyk et al., 2023). Analyses of commuting dynamics apply both SAM and SEM to understand the spatial variation in commuting distances and durations for different residential areas (K. Li et al., 2022). Urban congestion studies apply SDM to investigate how the congestion level of one road link is affected by characteristics of neighbouring links, such as road width, demonstrating spillover effects in traffic flow (Z. Zheng et al., 2024). Traffic safety research uses SDM to analyse how extreme weather events influence crash occurrences (Gu et al., 2025), and applies SEM to link crash frequencies with road length, speed limits, and residential demographics (Rhee et al., 2016). These applications demonstrate that spatial regression models are not merely technical extensions of standard regression but essential tools for accurately quantifying factor-traffic relationships in the presence of ubiquitous spatial dependencies. By explicitly modelling spatial structure, these approaches produce more accurate parameter estimates and richer substantive insights about how traffic patterns emerge from both local characteristics and broader spatial contexts.

3.2 Temporal Analysis

Urban traffic flow is not static but changes continuously through time, showing patterns and fluctuations that occur across multiple temporal scales. These include minute to minute variations within peak periods, hourly patterns throughout the day, daily differences between weekdays and weekends, seasonal cycles across the year, and long-term trends across years or decades. Understanding and predicting these temporal dynamics requires methodologies that are able to capture how current traffic conditions relate to past conditions, how traffic patterns repeat cyclically, and how traffic flows respond to time varying factors such as policy interventions. Temporal analysis applies these methodologies to identify temporal structure in time series data, and uses the identifies patterns to predict future traffic status. Over decades of methodological development, a wide range of models has been developed for traffic flow prediction (Y. Liu et al., 2025), which can be broadly grouped into four categories: statistical time-series models, machine learning models, deep learning models (H. Huang et al., 2022), large language models and foundation models (Long et al., 2025). These models represent a progression in methodological complexity and flexibility, from traditional approaches that rely on predefined statistical structures to advanced data-driven models capable of capturing complex, nonlinear, and high-dimensional temporal patterns in traffic data.

3.2.1 Statistical Time Series Models

Statistical time series models are built on the principle that temporal patterns in a dataset can be captured through structured mathematical relationships among past observations. The basic time series models assume that the traffic flows at time t depends linearly on the previous traffic flows with added random noise. One of the most commonly used statistical time series models is the autoregressive integrated moving average (ARIMA) model (Box & Jenkins, 1970; Jenkins, 1979; P. Newbold, 1983), which combines three components: an autoregressive (AR) term that forecasts the traffic flow by applying a linear combination of past traffic flows, an integrated (I) term that handles the non-stationary traffic flow prediction by applying differentiation, and a moving average (MA) term that models the error as a linear combination of past prediction errors. The ARIMA model has been widely used for short-term traffic flow forecasting (Dong et al., 2009; S. Lee & Fambro, 1999), demonstrating its effectiveness in capturing temporal dependencies and trends in traffic patterns. Nihan and Holmesland (1980) achieved approximately 5% error rates in predicting average weekday traffic flows, demonstrating that ARIMA models could capture the essential temporal structure of traffic data with reasonable accuracy. This foundational work established ARIMA as a benchmark against which subsequent methods would be compared.

Recognising that basic ARIMA makes limiting assumptions, particularly that temporal patterns remain constant across all time periods, researchers have developed numerous extensions that enhance the model’s flexibility and applicability to the complexities of traffic data. The seasonal ARIMA (SARIMA) model (Williams & Hoel, 2003) incorporates seasonal characteristics to account for periodic fluctuations in traffic flow. The space-time ARIMA (STARIMA) model (Pfeifer & Deutsch, 1980) introduces spatial dimensions to handle both spatial and temporal dependencies, making it particularly suitable for modelling traffic flow across multiple locations. The Kohonen ARIMA (KARIMA) model (Van Der Voort et al., 1996) classifies historical traffic flow patterns using a Kohonen self-organising map, and then forecast future traffic flow using a tailored ARIMA model for each class. The vector ARIMA (VARIMA) is a multivariate time series model (Athanasopoulos & and Vahid, 2008; de Silva et al., 2010; Sims, 1980) which is able to predict multiple traffic flows at different locations that may influence each other over time. The ARIMA with explanatory variables (ARIMAX) model (Box & Tiao, 1975) includes external covariates, such as weather or special events, to improve prediction performance by incorporating additional relevant information.

Another widely used model is the Kalman filter (Kalman, 1960; Kalman & Bucy, 1961), a dynamic model for state estimation that considers linearity and Gaussian noise, allowing for the prediction and correction of real values based on observed states (D. Feng et al., 2023). Rather than directly modelling observed traffic as a function of past traffic (as ARIMA does), the Kalman filter iteratively explores changes in unobserved states by comparing predicted and observed states to improve results. In the context of traffic prediction, Kalman filters are often used in real-time traffic monitoring and forecasting (F. Chen et al., 2012), providing updated predictions of traffic flow at each time step while accounting for noisy and incomplete sensor data (Abewickrema et al., 2023). Kumar (2017) has used only the previous two days of traffic observations with Kalman filters to predict the next day's traffic flow, achieving a mean absolute percentage error (MAPE) of around 10%. Kalman filters have also been integrated with a SARIMA plus Generalized Autoregressive Conditional Heteroscedasticity (GARCH) structure to improve the performance of short term traffic flow forecasting (J. Guo et al., 2014). Adaptive Kalman filters have been developed to update process variances dynamically (J. W. Gao et al., 2013; Ojeda et al., 2013), which improves performance under conditions of high traffic volatility.

Statistical time series models offer several important advantages for traffic flow prediction. They are built on well-developed theoretical foundations that provide a clear understanding of model behaviour and allow principled statistical inference. They are computationally efficient, which allows real time application even on modest hardware. They require relatively small datasets compared to methods that require large amounts of data, making them practical when extensive historical records are unavailable. However, these models also face important limitations. They assume linear relationships between past and future values, potentially missing nonlinear dynamics in traffic evolution. They typically require careful specification, such as selecting appropriate model orders, determining whether differencing is needed, and choosing which exogenous variables to include. They may struggle with disruptive traffic conditions, such as rapid changes in traffic patterns caused by incidents, events, or other disruptions that violate stationarity assumptions. These limitations have driven development of more flexible models that relax or eliminate these constraints.

3.2.2 Machine Learning Models

While traditional statistical time series models provide valuable frameworks for traffic flow prediction, their reliance on strong assumptions of linearity, stationarity (D. Xu et al., 2017) and predefined functional forms constrains their ability to capture the nonlinear (Nagy & Simon, 2018) and complex relationships inherent in real-world traffic data. They may be limited in adapting to sudden fluctuations caused by irregular events such as accidents or special events, which introduce rapid changes in traffic conditions that violate their foundational assumptions. To address these limitations, machine learning models have emerged as powerful alternatives, capable of learning complex, nonlinear relationships (Hassanpouri Baesmat et al., 2025) directly from data without relying on stringent parametric assumptions. Models such as K-Nearest Neighbours (KNN), Support Vector Machine (SVM), and Random Forest (RF) are adept at identifying hidden patterns (W. Wang et al., 2025) and interactions among various traffic-influencing factors (Casmin & Oliveira, 2025). Their data-driven attributes provide enhanced flexibility and adaptability, making them particularly effective in traffic forecasting scenarios where traditional methods may be less efficient.

KNN (G. A. Davis & Nihan, 1991; Yakowitz, 1987) is a simple, non-parametric regression algorithm that predicts future traffic states based on the most similar historical observations (S. Yu et al., 2019). It uses a distance measure (e.g., Euclidean distance) to identify the k closest historical traffic patterns (Y. Shi et al., 2022) to predict the next states of the traffic flow. The choice of the parameter k plays a crucial role in the model's performance (Fayed & Atiya, 2009), and various approaches have been proposed to determine the optimal value of k and reduce computational cost (Oh et al., 2016; D. Xia, Li, et al., 2016). Traffic flow applications of KNN have demonstrated its utility while also revealing opportunities for enhancement. S. Li et al. (2012) applied KNN to treat historical traffic flows recorded at the same clock time as potential neighbours and forecast future values. Y. Wu et al. (2015) integrated multi-linear analysis with KNN, defining distance metrics for tensor data to fully capture time variation, spatial correlations, and lane distribution characteristics within the traffic flow. Z. Liu et al. (2018) used KNN not for direct prediction but to improve the training process of neural network models by identifying and selecting historical state vectors similar to the current traffic conditions, thereby strengthening the mapping between inputs and outputs. Cai et al. (2020) introduced a sample-rebalanced, outlier-rejection KNN regression model that improves robustness against noisy and imbalanced datasets while retaining the strengths of traditional KNN.

SVM (Cortes & Vapnik, 1995) is a widely used machine learning method that can be used for both classification and regression tasks. The fundamental idea behind SVM is to transform the input data into a high-dimensional feature space (J. Tang et al., 2019), where it becomes easier to identify an optimal separating hyperplane. For regression tasks, the Support Vector Regression (SVR) variant is employed, which differs from standard SVM classification by aiming to find a hyperplane that minimises the total deviation of all sample points (G. Lin et al., 2022). To capture complex and nonlinear relationships between input features and target variables, SVR employs kernel functions. These functions implicitly map the original input data into a high-dimensional feature space where a linear relationship may hold even when the original input space exhibits nonlinearity. Commonly used kernel functions include the linear, polynomial, radial basis function (RBF), and sigmoid kernels (J. Tang et al., 2019; C.-H. Wu et al., 2009), each enabling SVR to model various types of nonlinearity without explicitly computing the transformation (G. Lin et al., 2022). In traffic flow prediction, SVR has been successfully applied to short-term forecasting by modelling complex nonlinear dependencies between traffic flow and its influencing variables (A. Cheng et al., 2017; W. Hu et al., 2016; N. Zhang et al., 2011). Researchers have integrated SVR with Bayesian classifiers for real-time traffic flow forecasting, achieving superior accuracy compared to linear regression methods (Ahn et al., 2016). Hybrid approaches combining SVR with optimisation algorithms have further enhanced performance. SVR was combined with a continuous ant colony optimization algorithm (SVRCACO) to enhance inter-urban traffic prediction, generating more accurate results than conventional time series models like SARIMA (W.-C. Hong et al., 2011). G. Lin et al. (2022) fused SVR with k-nearest neighbours and spatial time-delay analysis to better capture dynamic traffic states and spatial dependencies.

Random Forest (RF) (Breiman, 2001; Ho, 1995) is a robust supervised machine learning algorithm commonly applied to both regression and classification tasks (Belyadi & Haghighat, 2021). It belongs to the family of ensemble learning methods, as it constructs a large number of decision trees (Y. Liu & Wu, 2017) and combines their outputs to improve predictive performance and reduce the risk of overfitting (Barreñada et al., 2024). Each tree in the forest is built using a random subset of the training data and a random subset of features, introducing diversity among the individual trees and enhancing generalisation (L. Cheng et al., 2019). The model makes predictions by aggregating the outputs of all decision trees, typically through averaging in regression tasks. Several studies have explored the integration of RF with optimisation techniques and hybrid frameworks to improve forecasting performance. Hongren (2022) proposed a model that combines RF with the Cuckoo Search (CS) algorithm to optimise model parameters. Another study utilised RF to construct classification models for predicting traffic congestion states using a wide range of inputs, including weather, time, road quality, and holiday indicators (Y. Liu & Wu, 2017). To address temporal variations in traffic patterns, researchers also trained separate RF models for peak and non-peak periods, enabling the model to adapt to underlying trends even in the absence of explicit time information (Zarei et al., 2013). RF was also used as a feature selector within SVR-based frameworks, where it identified the most informative features before model training (L. Zhang et al., 2018).

Statistical machine learning approaches such as KNN, SVR, and RF share several strengths compared with classical statistical models. They can model nonlinear relationships without requiring explicit specification of functional forms. They can also capture complex interactions among multiple factors and adapt flexibly to patterns in data without strong distributional assumptions. In addition, they often achieve higher prediction accuracy on datasets with sufficient volume and complexity. However, these methods also introduce several challenges and limitations. They generally require larger training datasets than classical methods. They also produce models that are less interpretable, which makes it more difficult to understand why a particular prediction is made compared with transparent parametric models. Furthermore, they involve hyperparameters such as k in KNN, kernel choices in SVR, and tree number and depth in RF, which require tuning through validation procedures. In addition, they still treat temporal prediction mainly as a static mapping problem by incorporating time implicitly through input features rather than explicitly modelling temporal dynamics. This limitation motivates the development of deep learning models. These models are designed specifically for sequential data and allow models to represent how information changes over time, enabling the learning of complex temporal patterns directly from sequential observations.

3.2.3 Deep Learning Models

While machine learning models have demonstrated strong capabilities in capturing nonlinear relationships for traffic flow prediction, they typically rely on manually selected features (Boukerche & Wang, 2020) and may struggle to model long-term temporal dependencies or abrupt changes in traffic conditions over time. To overcome these limitations, deep learning models have emerged as powerful alternatives for traffic flow prediction, offering the ability to automatically learn temporal patterns from large-scale sequential data without predefined assumptions (Miglani & Kumar, 2019).

Recurrent Neural Networks (RNNs) (Cleeremans et al., 1989; Pearlmutter, 1989; Rumelhart et al., 1986) are a class of deep learning models specifically designed to handle sequential data (Y. He et al., 2024), making them well-suited for time series prediction tasks. RNNs incorporate a feedback loop that allows information from previous time steps to influence the current output (Boukerche & Wang, 2020). This temporal feedback structure enables RNNs to model dependencies across time and capture evolving traffic patterns. Traditional RNNs are effective at capturing short-term variations in traffic flow but often struggle with learning long-range dependencies due to vanishing or exploding gradient issues during training (Mienye et al., 2024). Some studies have explored the application of RNNs for traffic flow prediction, applying their capacity to capture sequential dependencies in time series data. X. Huang et al. (2023) proposed the Multi-Attention Predictive RNN (MAPredRNN) model which incorporates multiple attention mechanisms to extract temporal features of traffic closeness, periodicity, and trend, enabling more accurate short-term prediction in complex urban environments. To enhance optimisation and address convergence issues, Z. Liu et al. (2025) proposed an Improved Whale Optimization Algorithm integrated with RNN (IWOA-RNN), introducing advanced initialisation and reverse learning strategies to improve parameter tuning, robustness, and overall predictive performance. Additionally, the Time Slot RNN (TS-RNN) model (Qu et al., 2022) was developed to capture daily traffic flow fluctuations by learning distinct temporal sub-patterns, rather than modelling a complete time series holistically.

Long Short-Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) were developed to address the limitations of standard RNNs by introducing a gated memory architecture that facilitates the learning of long-term dependencies in sequential data. The architecture of an LSTM includes input, forget, and output gates (K. Liu & Zhang, 2021), which regulate the flow of information and allow the model to retain or discard past information as needed (Thakare et al., 2022). This makes LSTM particularly effective for traffic flow prediction, where patterns such as daily rush hours, weekly cycles, and temporal irregularities must be learned from historical data (Khan et al., 2021). In the context of temporal analysis, LSTMs have demonstrated strong predictive capabilities across various time horizons by dynamically adjusting to shifting traffic trends and handling noisy or incomplete sequences. Numerous studies have demonstrated the effectiveness of LSTM networks in capturing the temporal dynamics of traffic flow data. Tian and Pan (2015) first applied LSTM in traffic flow prediction and used the three multiplicative units in the memory block to determine the optimal time lags dynamically. Subsequent research tackled the challenges of variable-length sequences, irregular sampling, and missing values by using LSTM architectures that outperformed conventional methods in such noisy conditions (Y. Tian et al., 2018). To further enhance long-term temporal learning, bidirectional LSTM (Bi-LSTM) modules (H. Zheng et al., 2021) were employed to extract daily and weekly periodic features, allowing the model to understand variance patterns from both past and future contexts. Moreover, advanced hybrid models combining standard LSTM and Bi-LSTM layers (C. Ma et al., 2022a) were proposed to strengthen learning from sequential inputs, reduce prediction errors, and better capture long-term dependencies.

Gated Recurrent Unit (GRU) (Cho et al., 2014; J. Chung et al., 2014) is a more recent variant of RNNs designed to address the same long-term dependency challenges as LSTM, but with a simplified architecture (T. Lee & Singh, 2023). GRU combines the forget and input gates into a single update gate and merges the cell state and hidden state, which reduces the number of parameters (Salem, 2022) and improves computational efficiency. Despite its simpler structure, GRU performs comparably to LSTM in many traffic flow prediction tasks (T. Lee & Singh, 2023) and is particularly well-suited for scenarios requiring faster training or real-time inference. R. Fu et al. (2016) first applied GRU in traffic flow prediction, with the results showing that GRU significantly outperformed the statistical baseline in short-term traffic forecasting. Subsequent research expanded GRU's application by incorporating external factors such as weather conditions (D. Zhang & Kabuka, 2018), demonstrating that the inclusion of contextual variables further improved the model's predictive accuracy and reduced error rates. S. M. Abdullah et al. (2023) introduced bidirectional GRU-based architectures to classify traffic states, such as distinguishing between congested and non-congested periods. Another study tuned the GRU model by introducing algorithms to optimise hyperparameters and sliding window size (Hussain et al., 2021), which led to improved forecasting performance on real-world traffic datasets.

More recently, transformer-based architectures have been introduced to traffic flow prediction, offering an alternative to recurrent networks by relying on self-attention mechanisms rather than sequential processing. Unlike RNNs, LSTMs, or GRUs, transformers do not depend on recursive structures to capture temporal dependencies. Instead, the self-attention mechanism enables the model to directly relate information across all time steps, which is particularly advantageous for learning long-term dependencies and handling irregular or complex temporal sequences (Vaswani et al., 2017). In traffic flow prediction, this allows transformers to effectively capture both short-term fluctuations and long-term periodic patterns while maintaining high computational efficiency through parallel processing. Empirical studies have demonstrated their potential in transportation research. Reza et al. (2022) presented a multi-head attention-based transformer model for traffic flow forecasting using the PeMS dataset, comparing its performance with GRU and LSTM models. The model employed five heads with multiple encoder–decoder layers and square subsequent masking techniques, achieving superior accuracy in long-term traffic prediction after being trained on large-scale data. Jiang et al. (2023) proposed a Propagation Delay-aware Dynamic Long-range Transformer (PDFormer), which was tested on six real-world traffic datasets. Their results demonstrated that PDFormer not only achieved state-of-the-art predictive accuracy but also offered competitive computational efficiency. Xu et al. (2021) introduced Spatial-Temporal Transformer Networks (STTNs), which incorporate directed spatial dependencies and long-range temporal dependencies to enhance long-term forecasting performance. Their experiments on the PeMS-Bay and PeMSD7(M) datasets confirmed that STTNs significantly outperformed baseline models, particularly in predicting long-term traffic flows.

Deep learning models such as RNNs, LSTMs, GRUs, and transformers represent the current state of the art for traffic flow prediction and often achieve accuracy levels that classical statistical and traditional machine learning methods struggle to match, particularly for complex datasets and long forecast horizons. Their ability to automatically learn hierarchical temporal representations from raw sequences reduces reliance on manual feature engineering, while their flexible architectures allow them to adapt to diverse patterns and scales. However, these advantages also introduce several challenges. Deep learning models typically require substantially larger training datasets than simpler alternatives. Training these models also demands considerable computational resources and technical expertise. Furthermore, these models may not generalise well to conditions that differ significantly from the training data. These limitations motivate ongoing research into methods that combine the flexibility of deep learning with improved data efficiency and generalisation. This effort has led to the emergence of large language models and foundation models designed for time series prediction.

3.2.4 Large Language Models and Foundation Models

The most recent development in temporal analysis methodology represents a paradigm shift. Instead of training models from scratch on task specific traffic datasets, researchers are exploring whether large language models (LLMs) that are pre-trained on extremely large datasets, can be adapted or directly applied to traffic flow forecasting by using knowledge learned during pre-training. LLMs, such as GPT (Radford et al., 2018) and BERT (Devlin et al., 2019), are based on the transformer architecture, originally developed for natural language processing (NLP). These models are trained on large amounts of textual data and can generate, summarise, and reason over language with remarkable generalisation capabilities. They are particularly effective at capturing contextual dependencies over long sequences, which has inspired researchers to explore their application beyond text, including in time series forecasting (TSF). Early research concentrated on adapting LLMs for structured sequential data (X. Liu & Wang, 2024), specifically tackling the technical challenge of formatting time series inputs in a way that existing LLM architectures could process effectively. LLMTIME (Gruver et al., 2024) introduced a specialised tokenizer to encode time series inputs for models like GPT-3 (Brown et al., 2020), enabling zero-shot forecasting without requiring historical data from the target domain. Although LLMTIME showed limited performance and struggled with long input windows, subsequent models such as AutoTimes (Y. Liu, Qin, et al., 2024) have improved on these limitations, supporting longer contexts and offering more robust forecasts.

Time series data are frequently characterised by inconsistencies, fluctuations, and missing values, which makes LLMs a valuable tool due to their practical advantages. Models like Time-LLM (Jin et al., 2024) and LSTPrompt (H. Liu, Zhao, et al., 2024) use strategies such as patching and context integration (CI) to align time series representations with textual prompts, allowing for cross-modal learning and effective few-shot forecasting. Time-LLM also minimises fine-tuning costs by requiring only small additional modules with relatively few parameters. FPT (T. Zhou et al., 2023) enhances adaptability by freezing the core attention blocks of the transformer while only training the embedding and normalisation layers, improving domain flexibility. Similarly, LLM4TS (Chang et al., 2025), TEST (C. Sun et al., 2024), and TEMPO (Cao et al., 2024) introduce refined tokenisation strategies and patch-based input structures to better capture temporal dynamics. However, these approaches remain constrained by the fact that LLMs are originally pre-trained on text data rather than numerical time series, which may limit their ability to fully capture the continuous and numerical nature of temporal patterns.

More recently, a second research direction focuses on constructing foundation models specifically for time series tasks from the ground up. To overcome the limitations of LLM based approaches, these models retain similar transformer based architectures but are pre-trained directly on large scale time series data, making them more suitable for capturing temporal patterns. This approach shifts the focus from adapting text-based models to learning representations of temporal patterns directly from numerical sequences. TimeGPT-1 (Garza et al., 2024) is the first pre-trained foundation model developed using a large volume of time series data from diverse domains. This GPT-based model can generate accurate forecasts for different datasets without additional training. Building on this foundation, Lag-Llama (Rasul et al., 2024) adopts a decoder-only transformer architecture and constructs lagged features from prior values in the time series, allowing the model to capture temporal dependencies without relying on positional encodings typically used in natural language processing. TimesFM (Das et al., 2024) employs a patch-based tokenisation and is pre-trained on a large-scale time series corpus. It demonstrates strong zero-shot forecasting capabilities across varying input sequence lengths, prediction horizons, and temporal granularities, offering robust performance across diverse application domains. Chronos (Ansari et al., 2024) adopts a similar strategy by training language models from scratch using a large time-series corpus comprising both real-world and synthetic datasets. The data are tokenised through scaling and quantisation, which enables Chronos to better capture temporal patterns, avoiding limitations associated with adapting models originally designed for natural language.

For traffic flow prediction, these large language model and foundation models offer several potential advantages. They may improve data efficiency because models do not need years of historical traffic data from a specific location to achieve accurate predictions. Zero shot or few shot approaches may produce useful forecasts with only limited local data by using patterns learned from diverse pretraining datasets. These models may also generalise across different contexts. For example, a foundation model trained on traffic data from many cities may generate accurate forecasts for new cities without additional city specific training. Besides, these models may reduce implementation barriers. Organisations that lack machine learning expertise or the computational resources required to train deep neural networks may still be able to apply pretrained models directly.

These potential advantages encourage further exploration of foundation models for traffic flow forecasting, although important gaps in understanding still remain. Foundation models have demonstrated zero shot forecasting ability on benchmark time series datasets, but their performance on traffic specific prediction tasks remains largely unexplored. This limitation is especially important under disruptive conditions that significantly change traffic patterns. The COVID 19 pandemic created unprecedented disruptions to urban traffic around the world and therefore provides a valuable test case. An important question is whether foundation models that are pre-trained on diverse time series can generalise to predict traffic flows during periods when normal patterns are interrupted. Evaluating whether zero shot forecasting maintains accuracy under both normal and disruptive conditions can help clarify the practical value of foundation models for real world traffic applications. This gap between the potential of foundation models and their limited evaluation in traffic forecasting under varied conditions highlights an important opportunity to examine how these advanced methods perform in a critical urban analytics domain.

3.3 Chapter Summary

This chapter has reviewed the methodological approaches available for analysing and predicting urban traffic flows, structured across two broad categories: regression models and temporal prediction models. The review identifies the limited application of these models and the lack of systematic evaluation of their performance under disruptive traffic conditions. In addition, the use of foundation models remains underexplored as an alternative to task-specific deep learning systems in real-world urban traffic prediction contexts.

Chapter 4 High-resolution traffic flow data from the urban traffic control system in Glasgow[1]

This chapter aims to construct a high-resolution, city-scale traffic flow dataset for Glasgow covering four consecutive years before, during, and after the COVID-19 pandemic. Specifically, a multi-step data cleaning process is developed and applied to remove poor-quality sensor records using spatial, temporal, and numerical filtering criteria. The dataset covers hourly traffic flows across all road classes in the Glasgow City Council area, providing broad spatial coverage and fine-grained temporal resolution that are not available in existing publicly accessible traffic datasets for UK cities. The work presented in this chapter provides the empirical foundation for the spatial econometric analysis in Chapter 5 and the traffic flow prediction in Chapter 6, demonstrating how high-resolution sensor data can be systematically cleaned, validated, and prepared for downstream urban mobility analysis.

4.1 Background & Summary

In most cities, motor vehicles dominate the transportation system (Transport Scotland, 2019), which causes a series of challenges, such as traffic congestion, air pollution, and road accidents. Those traffic-related issues cause significant challenges in urban residents' daily lives, and the solutions are still unclear (Alkaabi, 2023; Shr et al., 2023; S. Singh et al., 2023). To address these issues, the first step is to capture and understand the traffic flow information of motor vehicles in urban areas. To obtain such information, local governments have implemented Intelligent Transportation Systems (ITSs), incorporating diverse urban sensing technologies, including induction loop coil sensors on the road surface, above ground thermal and CCTV cameras. This system generates traffic flow data, enabling monitoring urban traffic flow patterns in high spatiotemporal resolution.

Traffic flow data has been widely applied in human geography, transportation engineering and management, urban planning, and public health (Kang et al., 2020). It reflects the carriageway occupancy (Glasgow City Council, 2023; Mon et al., 2022) and records the number of motor vehicles at the road network level, indicating traffic congestion and underlying socioeconomic environments (Kang et al., 2020). In transportation applications, traffic flow data has been used to study traffic surveillance, management, and prediction.

[1] Li, Y., Zhao, Q., & Wang, M. (2025). High-resolution traffic flow data from the urban traffic control system in Glasgow. Scientific Data, 12(1), 253. https://doi.org/10.1038/s41597-025-04494-y

In traffic surveillance, such data helps recognise traffic hotspots, identify traffic congestion, and monitor accident-prone areas (F. Yu et al., 2023). Based on the surveillance, the local government manages the traffic by optimising traffic signal timings, providing alternative routing suggestions, and implementing safety measures. Moreover, future traffic conditions can be predicted by analysing historical traffic flow data and real-time traffic management.

As pointed out by several studies (Y. Gao & Levinson, 2022; Z. Liu & Stern, 2021; Reza et al., 2022), traffic flow data plays a key role and serves as a data foundation in analysing travel behaviours and patterns. Although some studies have released a set of traffic flow-related open datasets (Mon et al., 2022; Y. Wang et al., 2023) for urban traffic analysis, these datasets lack three major aspects. First, long-term traffic flow data is lacking at high temporal granularity. For instance, some datasets only provide traffic flow data at an annual level (Department for Transport, 2023; van Strien & Grêt-Regamey, 2024), while some studies generate datasets in 5-minute intervals but only for one month (Y. Wang et al., 2023). Second, satisfactory spatial coverage at a city scale is not available. Most openly available datasets provide traffic flow information around the city centre or motorways, which always shows high traffic volume (Mon et al., 2022). Higher spatial coverage datasets provide more detailed traffic patterns over the entire city, which are necessary to more accurately characterise heterogeneous relationships between mobility patterns of vehicles and surrounding socioeconomic environments within cities. Third, the quality and accuracy of data generated by ITSs are not controllable, especially for long-term traffic flow data. Various factors, including sensor precision, environment conditions, and algorithm complexities, can lead to unpredictable inaccuracies in the data.

To address the limitations of existing traffic flow datasets, we introduce an openly available dataset that provides city-scale traffic flow data within Glasgow City for four consecutive years from October 2019 to September 2023. This chapter proposes a workflow to improve the quality of datasets via spatial and temporal data cleaning and processing. The traffic flow data has been collected via a network of sensors placed on street furniture or under the road surface itself (Glasgow City Council, 2023). The sensors are placed along roads ranging from motorways to local roads, encompassing all categories from main roads to fifth-class roads in the UK, and they record the traffic flow every 15 minutes. The dataset developed in this chapter holds great potential for various research directions and downstream applications. Here are some potential benefits and applications:

- Traffic dynamic analysis at the intra-city scale. Researchers can conduct in-depth analyses of traffic patterns within the city, identifying (off) peak-hour trends, seasonal variations, and annual patterns.

- Traffic management and infrastructure planning. By analysing the traffic flows and their surrounding built environment, city planners and transportation agencies can optimise traffic signal timings, enhance road infrastructure, and manage congestion.

- Urban environment improvement. This four-year dataset can aid in assessing the environmental impact of traffic flows, helping researchers understand the relationship between transportation patterns and air quality and improving the urban environment.

4.2 Study Area

Glasgow is the largest city in Scotland, located on the banks of the River Clyde in west central Scotland. It covers a total area of 175 km ^{2}(Glasgow City Council, 2020), which represents the administrative area managed by Glasgow City Council. The city is divided into 23 electoral wards and 56 recognised neighbourhoods (Glasgow City Council, 2024b), each with its own local characteristics and urban functions. Glasgow has a temperate oceanic climate and is known for its high levels of rainfall. There are an average of 170 rainy days per year in Glasgow, making it the rainiest city in the entire United Kingdom (Scotland City Tours, 2019). Besides, Glasgow is well known for its generous amount of public greenspace. More than 3,500 hectares of Glasgow is greenspace, and there are 91 parks distributed throughout the city (Glasgow City Council, 2017). The name Glasgow comes from the Gaelic word "Glaschu," which means "Dear Green Place", directly reflecting the proud history of creating and protecting greenspace in this city (Glasgow City Council, 2019).

Glasgow City Region (GCR) is the fourth-largest city region in the UK, comprising Glasgow City and seven surrounding council areas. The region has a population of approximately 1.8 million people, accounting for around one-third of Scotland's total population (Ministry of Housing, Communities & Local Government, 2025). Within GCR, Glasgow has the most population in Scotland as a city. As of 30 June 2023, the estimated population was 631,970, which is an increase of 1.6% (9,920 people) compared to the previous year (National Records of Scotland, 2024). Glasgow also has the highest population density in Scotland (Scotland's Census, 2023). There are 3,562 people living in each square kilometre in Glasgow, compared to just 70 per km ²across Scotland overall (Glasgow City Council, 2020). Glasgow is also more ethnically diverse than most other areas in Scotland. Around 19.3% of people living in Glasgow are from Black and Minority Ethnic (BME) backgrounds, which is nearly three times higher than the Scottish average of 7.1%.

Glasgow is the main economic centre in Scotland and plays a key role in driving the national economy (Glasgow City Council, 2024c). It is not only the economic engine of the city region but also one of the most important commercial hubs in the UK outside of London (Glasgow City Council, 2017). Glasgow's Gross Value Added (GVA) has increased every year since 2010, contributing £22.8 billion to the Scottish economy in 2019. Although the COVID-19 pandemic created economic challenges, Glasgow has maintained strong performance in business and become one of the fastest growing tech investment hubs in the UK (Hatton, 2021). In 2021, tech companies based in Glasgow attracted £105 million in venture capital, which was a 59% increase from £43 million in 2020 (Glasgow City Council, 2024c).

4.2.1 Transportation System in Glasgow

Glasgow has the largest number of vehicles licensed among all local authorities in Scotland, with 212,064 vehicles licensed at the end of 2023 (Transport Scotland, 2025). However, Glasgow had the lowest rate of vehicle ownership, with only 388 vehicles per 1,000 people aged 17 and over. Despite lower per capita ownership, the city recorded the highest traffic volumes in Scotland, accounting for 7.4% of all traffic on the road networks. In 2022, road vehicles in Glasgow consumed 277.4 thousand tonnes of oil equivalent (ktoe) of petrol and diesel, which was the highest fuel consumption in Scotland. Traffic safety has improved over time in Glasgow, with the number of recorded collisions falling to 569 in 2023, which is less than half of that reported in 2016 (Transport Scotland, 2025).

In recent years, travel behaviour in Glasgow has gradually changed, with people increasingly using more sustainable and flexible forms of transport. In 2022, 38% of people in the city commuted by car, while 14.2% used public transport and 11% walked or cycled to work. The other 33.3% of people worked from home, reflecting the lasting influence of the COVID-19 pandemic on daily mobility patterns (Understanding Glasgow, 2025). Active travel has shown long-term growth in Glasgow. Between 2009 and 2021, trips into the city centre by bicycle increased by 165%, while pedestrian trips increased by 19% between 2009 and 2018. Although walking rates declined sharply during the pandemic and have not fully returned to pre-pandemic levels, active travel remains an important part of daily life in Glasgow. In 2023, 54% of school children in the city travelled to school by active means, with 48% walking and 5.7% cycling, scooting, or skateboarding (Understanding Glasgow, 2025b). Meanwhile, public transport usage is recovering. The number of passenger journeys on the Glasgow Subway increased by 47% between 2021–22 and 2022–23 (Transport Scotland, 2025).

Although Glasgow City Council has made good progress in recent years to promote sustainable transport, air quality in the city centre remains a concern. In particular, nitrogen dioxide (NO_2) concentrations continue to exceed legal limits at several monitoring locations in city centre (Glasgow City Council, 2025b). Since road traffic is the main source of this harmful pollutant, Glasgow City Council introduced the Low Emission Zone (LEZ) as a key measure to reduce vehicle emissions and protect public health, especially for vulnerable populations (Glasgow City Council, 2025b). Glasgow's LEZ officially came into force on 1 June 2023 and applies to all vehicles entering the defined city centre area. Unlike congestion charging schemes in other cities, drivers cannot pay to enter a LEZ in Scotland. Instead, all vehicles entering the city centre zone area must meet the less-polluting emission standards. Non-compliant vehicles are subject to an initial penalty charge of £60, which doubles with each subsequent breach. However, this surcharge only applies once the first penalty charge notice (PCN) has been delivered to the vehicle's registered keeper. Charges are capped at £480 for cars and light goods vehicles, and £960 for buses and heavy goods vehicles (Glasgow City Council, 2025c). The LEZ operates 24 hours a day throughout the year, and covers approximately one square mile of Glasgow’s city centre. The boundaries are defined by the M8 motorway to the north and west, the River Clyde to the south, and Saltmarket/High Street to the east (Glasgow City Council, 2024a).

Emerging evidence suggests that the LEZ is already having measurable effects on both traffic patterns and air quality. An evaluation of pre-LEZ (Aug–Sep 2022) and post-LEZ (Aug–Sep 2023) conditions found significant decreases in traffic flow on High Street during weekdays, alongside significant reductions in NO_2 levels across all days. At Hope Street within LEZ, despite no significant change in traffic volumes, NO_2 concentrations also declined significantly across all days (Shin et al., 2024). These findings highlight that the LEZ is contributing to improvements in air quality, with health and environmental benefits likely to become more evident as the policy develops and more motor vehicles transition to electric vehicles.

4.2.2 COVID-19 and Mobility Restrictions in Glasgow

The Scottish Government implemented a series of public health and mobility restrictions in response to the COVID-19 pandemic beginning in mid-March 2020. Initial measures on 16 March included advice on working from home and avoiding large gatherings and non-essential travel. These were quickly followed by the closure of all pubs, bars, and restaurants on 20 March, and the issuance of shielding advice for vulnerable individuals on 22 March. A nationwide lockdown was introduced on 23 March, limiting travel to essential purposes only, such as food shopping, medical needs, and daily exercise. Over the following months, a phased approach to easing restrictions was adopted. Key policy documents such as the COVID-19 framework for decision making (23 April) (First Minister, 2020a), Scotland's route map (21 May) (First Minister, 2020b), and the Transport Transition Plan (26 May) (Scottish Government, 2020) guided the gradual reopening process. Phase one of easing began on 29 May, with phases two and three following on 19 June and 10 July respectively, permitting the reopening of non-essential retail, hospitality, and cultural venues. Face coverings became mandatory on public transport from 22 June. Despite this gradual reopening, several localised restrictions were reinstated due to regional outbreaks, including household gathering bans in areas like Glasgow in September. By November, a five-level tiered restriction system was introduced, with most central authorities placed under level 3 or 4 restrictions. A temporary relaxation of household rules was permitted on Christmas Day 2020, but strict level 4 measures resumed across mainland Scotland on 26 December. The second national lockdown began on 5 January 2021, followed by a phased return to in-person schooling on 22 February (Transport Scotland, 2021a). On 26 April 2021, Scotland moved to Level 3 restrictions, allowing the reopening of hospitality venues and tourist accommodations. Further relaxations followed as the legal requirements for physical distancing and limits on gatherings were removed on 8 September 2021. International travel restrictions were lifted entirely on 18 March 2022, and the legal mandate to wear face coverings on public transport and in most indoor settings ended on 18 April 2022 (Scottish COVID-19 Inquiry, 2023).

4.3 Methods

Figure 4-1 illustrates the detailed process involved in generating the traffic flow dataset. Initially, we collect the raw traffic flow data through the Glasgow open data portal (Glasgow City Council, 2022) (https://gcc.developer.azure-api.net/api-details#api=traffic&operation=5b044adda611ad4c9b1c58b2), which provides several open data Application Programming Interfaces (APIs) by the Glasgow City Council. This dataset is derived from a network of over 1000 sensors positioned along roads, capturing traffic information at 15-minute intervals. To refine the dataset, we implemented a two-fold filtration process based on spatial and temporal constraints. Initially, data is filtered according to the sensors placed, narrowing the scope to specific geographical areas and locations. Subsequently, a temporal constraint is applied to refine the dataset based on the study period and 15-minute intervals. Then, we examined the specific information in the records for the remaining sensors. In this study, each record refers to the traffic flows captured by the sensors at one-time intervals. Sensors with a substantial proportion of irregular traffic flows or incorrect time intervals are excluded from the dataset. The final step involves reconstructing and aggregating the cleaned traffic flow data. This process ensures that the data adheres to the specific time intervals and formatting requirements, resulting in an accurate and reliable dataset for downstream applications.

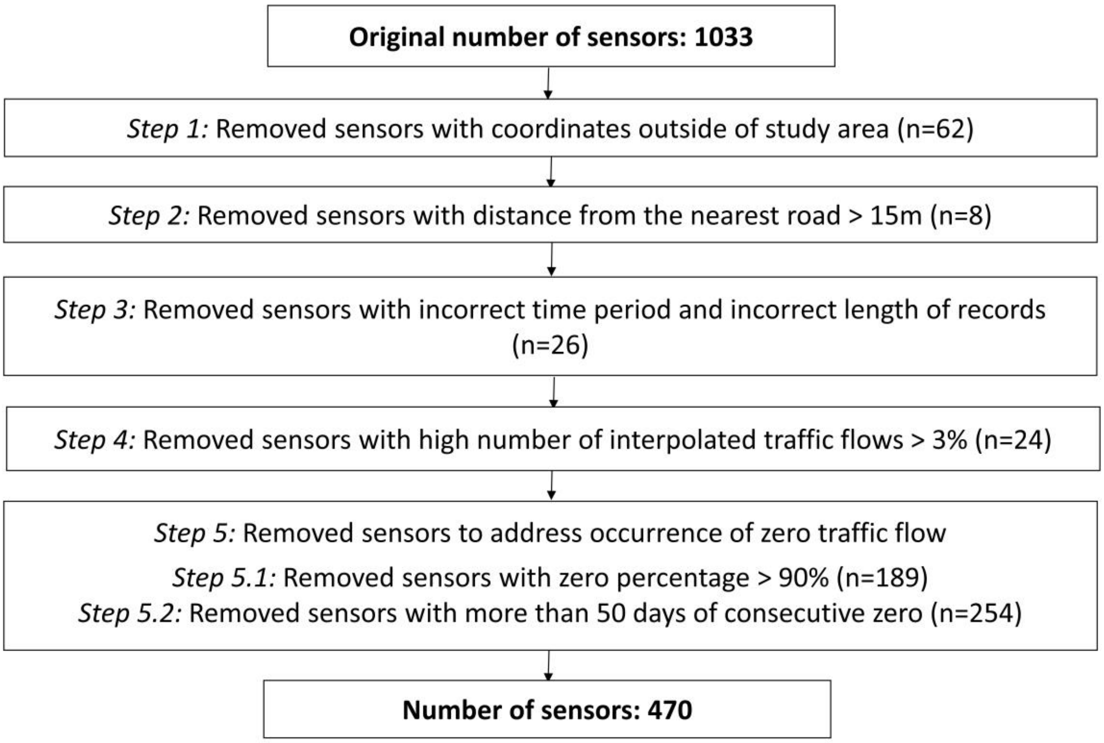

Figure 4-1. Data cleaning flowchart.

4.3.1 Original data Sources

The original traffic flow data in Glasgow is provided by Glasgow City Council through its open data portal (Glasgow City Council, 2022) (https://gcc.developer.azure-api.net/api-details#api=traffic&operation=5b044adda611ad4c9b1c58b2). Glasgow City Council manages infrastructure to monitor and control real-time traffic flow data across the city streets. The data is collected via a Split Cycle Offset Optimisation Technique (SCOOT) based Urban Traffic Control (UTC) system (Glasgow City Council, 2023). The most common sensors SCOOT uses are ones buried in the road surface, such as an inductive loop or mounted above ground, usually on top of the signal post, such as microwave vehicle detectors. Inductive loops collect traffic flows by analysing the electromagnetic effects caused by the presence or passage of a vehicle (Department for Transport et al., 2019). Specifically, when a vehicle passes the inductive loop, SCOOT converts the information into a "link profile unit" (lpu), which is a hybrid of traffic flow and occupancy. The unit used by SCOOT in its calculations is called "Cyclic flow profiles", which is the lpu signals over time that are constructed for each link. This study has a total of 1033 sensors collecting the traffic flows for four years from October 2019 to September 2023. The detailed spatial density distribution of the physical sensor placement is shown in Figure 4-2. The sensors are located from the main roads (motorways) to the fifth-class roads (local roads) in Glasgow, recording the traffic flows at 15-minute intervals. This extensive sensor network provides widespread coverage of the city’s diverse roads, contributing to an in-depth analysis of traffic patterns and surrounding built environments.

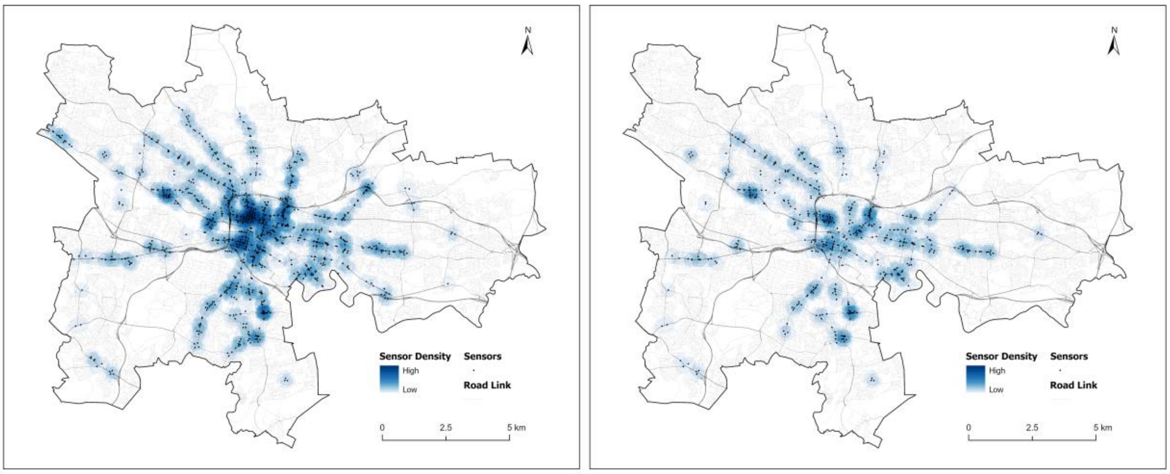

Figure 4-2. Spatial distribution of original(left) and filtered(right) traffic sensors in Glasgow.

4.3.2 Data Refinement

Since the raw traffic flow data is collected via the automatic traffic control system sensors, inspecting and cleaning the dataset before proceeding with any downstream analysis is necessary. In practice, the most common errors in the raw sensor data are missing data and faults (Teh et al., 2020), such as outliers. Based on this, our first assumption is that most errors can be identified and removed as outliers. A second assumption is applied during this data refinement. We assume each active sensor should record at least one vehicle per day, so sensors consistently recording zero are treated as inactive and excluded. A third assumption is that the retained sensors are representative of the original sensors. This is validated in Section 4.5.1. We first filter the data according to the sensors placed with spatial and temporal constraints.

Step 1. The coordinates of each sensor are extracted, and a comparison is made with the geographic boundaries defining the Glasgow City Council area. Sensors located outside this specific area are deemed beyond the scope of the research and consequently excluded from further steps.

Step 2. We consider the spatial relationship between traffic flows and the road network. This process evaluates the proximity of the sensors to the city's road infrastructure. Since sensors record traffic flows in Glasgow along the road network, it is essential to consider the range of Euclidean distances from each sensor to its nearest road. In Glasgow, over 99% of sensors are placed within a 15-meter radius of roads. Only eight sensors deviate by 20 meters or more, resulting in their exclusion from the dataset.

Step 3. We implement temporal filtering on the traffic flow data. The dataset in this study spans from October 1st, 2019, to September 30th, 2023, including a total of 1461 days. Sensors with traffic flows starting later than October 2019 or ending before September 2023 are excluded from the dataset. With a 15-minute collection interval, each sensor theoretically generates 140246 records. Five sensors that lacked valid data for over half the period were removed from this dataset. 99.4% of sensors operate typically, showing a loss of less than 5% of traffic flows over the four-year duration. Overall, 26 sensors are excluded based on the temporal constraint.

Step 4. After completing the spatial and temporal inspections detailed above, the traffic flow data undergoes numerical filtering. Glasgow City Council has implemented an interpolation method for instances without data returns. This method duplicates the number of flows from the latest to the current timestamp to address the absence of valid data. Subsequently, 24 sensors in Glasgow were identified and removed due to having more than 15% interpolated data, while the remaining sensors exhibit interpolation levels below 3%.

Step 5. The most prevalent data issue in the time-series dataset is the occurrence of zero traffic flow values. These zeros indicate extended periods when no vehicles pass a particular road, lasting for hours or even days. We address this issue by analysing zero traffic flow from two different aspects.

Step 5.1. First, we assess the frequency of no-data records for each sensor. We calculate each sensor's overall percentage of zero traffic flow values across all four-year records. We exclude 189 sensors that showed a high frequency of no-data, with more than 90% zero traffic flow during the four years.

Step 5.2. Next, we focus on long and continuous periods of no-data events. For each sensor, we identify all the entire natural days with 24 hours of zero traffic flow. This step assumes that at least one vehicle should pass each sensor daily in Glasgow. The number of no-data natural days for each sensor varies across sensors, ranging from a maximum of 1164 to a minimum of 50 days. To ensure data integrity and completeness, we retain only sensors with 50 days of no-data events. After this refinement, a total of 470 sensors are included in the dataset, with each sensor recording 1,411 days of data out of 1,461 days across four years. Sensors removed in Step 5 are shown in Figure 4-3.

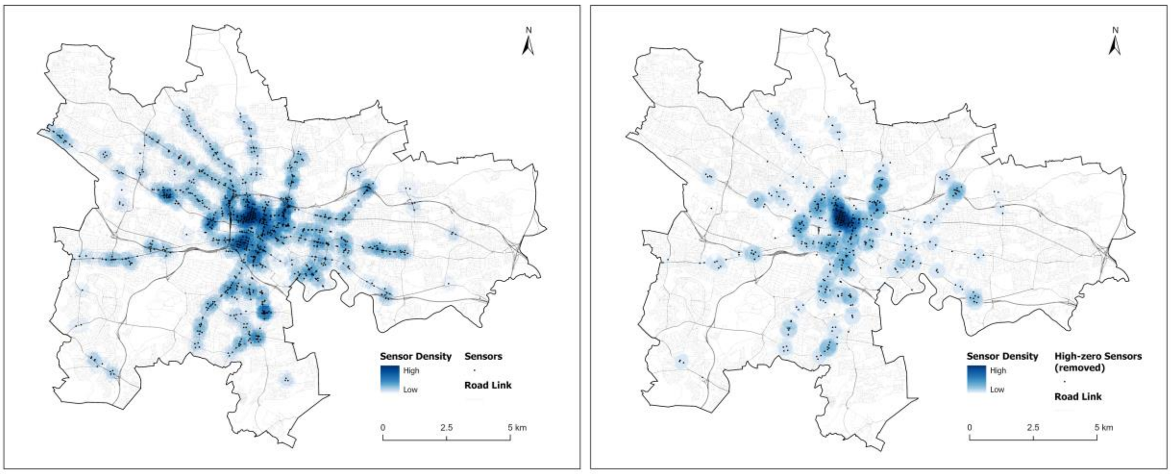

Figure 4-3. Spatial distribution of original traffic sensors (left) and high-zero traffic sensors removed in Step 5 (right) in Glasgow.

4.3.3 Data Aggregation

In this study, we reconstruct and aggregate the raw traffic flows hourly. Specifically, we eliminate the interpolated records for each retained sensor, replacing them with NaN (Not a Number) traffic flow values. The hourly traffic flows are aggregated by first computing the average value for each hour. This computation ignores NaN values, and the flows are averaged based on the valid number of records. For instance, if two valid flows are available for 8 AM on August 16th, 2021, the sum of the two records is divided by two. Then, we multiplied the averaged flows by four, as each hour should ideally have four records with a 15-minute interval. An hour with four invalid records is removed from the data, as the aggregation result is considered invalid. We will not include any invalid NaN values in the final datasets.

In particular, the zero values of the retained 470 sensors are kept, as their occurrence is considered reasonable, as illustrated in Figure 4-4. Figure 4-4 is a box plot illustrating the zero-flow frequency for each sensor over four years, segmented by each hour of the day. Figure 4-5 is a heat map showing the frequency of zero flow events, where the x-axis represents the hours of the day over four consecutive years, and the y-axis corresponds to each sensor. Since traffic flow data collection began in October 2019, the zero-flow frequency is relatively low in 2019 due to the limited data volume. Figure 4-5 shows that the zero-flow frequency was higher in 2020 and 2021 compared to 2022 and 2023 due to the mobility restrictions during the COVID-19 pandemic. This pattern supports the validity of the observed zero flow events in the remaining dataset. Both the line plot and the heat map demonstrate that, for most sensors, zero traffic flows were recorded before 6 AM and after 11 PM. Specifically, 3 AM was the quietest time in Glasgow. Sensor GH3451_L (highlighted in Figure 4-5), located at the car park entrance of Emirates Arena, exhibited the highest zero flow frequency at 3 AM for four consecutive years. This indicates that no vehicles came to Emirates Arena at 3 AM for more than 88% of the recorded days. The busiest time in Glasgow was around noon, with over 99% of days showing traffic flows during this period.

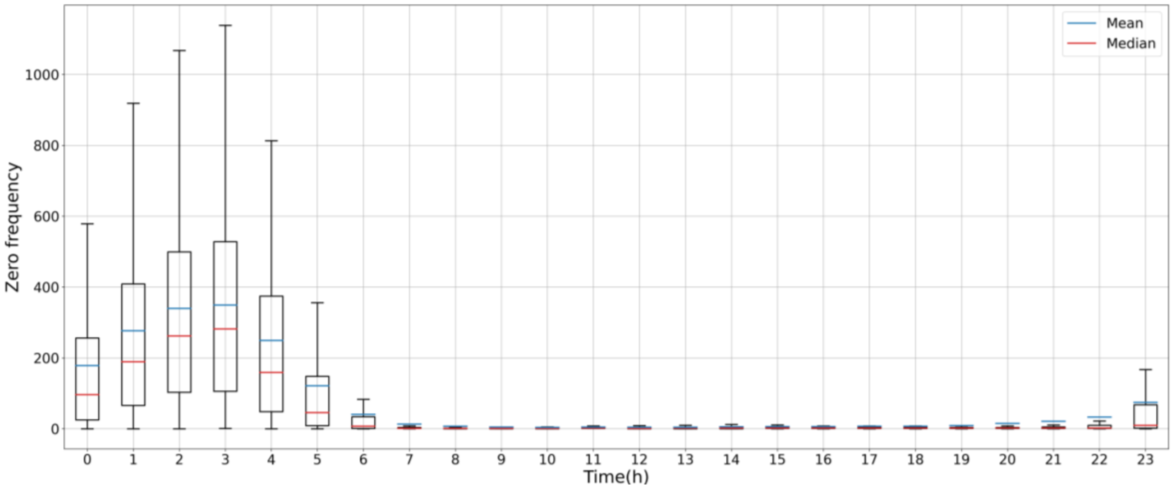

Figure 4-4. Boxplot of hourly zero flow frequency.

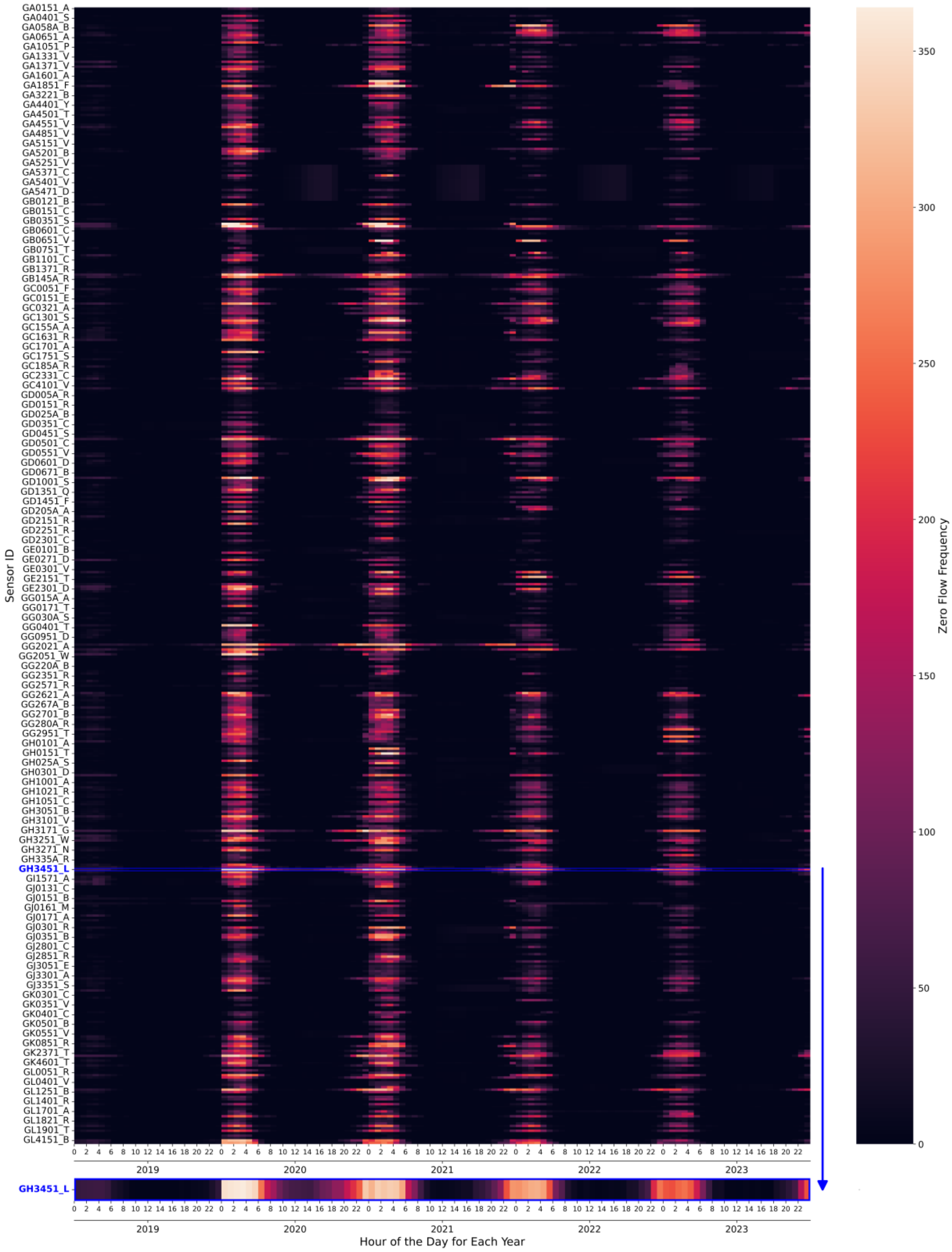

Figure 4-5. Heatmap of hourly zero flow frequency.

4.4 Data Records

The dataset is available from a long-term Zenodo repository (L. Yue et al., 2024). The records of this dataset are compiled using three main products. The first contains 470 files, each containing a sensor's hourly traffic flow data from October 1st, 2019, to September

30th, 2023. The second product is a single file providing geographical information for 470 sensors. The third product is a single file that includes binary results for each data cleaning step applied to the original 1033 sensors, including their geographical information as well. All files are formatted in comma-separated values (CSV), a widely employed format for publicly storing, transferring, and sharing data.

4.4.1 Original sensor status

This file provides information on the status of sensors through multiple data cleaning steps, including their unique ID, geographical coordinates (latitude and longitude), and binary results for each step (steps 1 to 5.2). Each row in the file represents a sensor, specifying whether it was remained or removed at current step of the analysis. The removed sensors are marked with a value of 0, while the remaining sensors are marked with 1. This structured file helps researchers understand the filtering process and identify sensor issues across different steps. The attributes of the file are presented in Table 4-1.

File name	Column name	Description
status.csv	id	Unique ID for each sensor, e.g., GA0601_T.
	latitude	The Latitude in decimal degrees of WGS84 coordinates, e.g., 55.86238129.
	longitude	The Longitude in decimal degrees of WGS84 coordinates, e.g., -4.26570708.
	step 1	The status of sensors at the current step is 1 if retained and 0 if removed.
	step 2	
	step 3	
	step 4	
	step 5.1	
	step 5.2	

Table 4-1. Description of sensor status attributes.

4.4.2 Sensor locations

This file provides sensor information, including ID and the corresponding geographical coordinates. Each row in the file includes details about a sensor, specifying the unique ID with the Longitude and Latitude coordinates in the WGS84 projection system. By mapping the spatial distribution of sensors across Glasgow, researchers can gain insights into various studies, such as analysing spatial patterns, identifying hotpots, and understanding the impact of geographical features on built environments. Table 4-2 shows the attributes of sensor locations.

File name	Column name	Description
locations.csv	id	Unique ID for each sensor, e.g., GA0601_T.
	latitude	The Latitude in decimal degrees of WGS84 coordinates, e.g., 55.86238129.
	longitude	The Longitude in decimal degrees of WGS84 coordinates, e.g., -4.26570708.

Table 4-2. Description of sensor location attributes.

4.4.3 Traffic flows

Traffic flow data consists of 470 files, each corresponding to a specific sensor and covering four years. Table 4-3 describes the files, while Table 4-4 provides data attributes. Each row in the files contains information about the specific date and time the traffic flow data was collected. There are 50 missing days in this dataset for four years from October 1st, 2019, to September 30th, 2023. Table 4-5 details the missing days for all the sensors in the traffic flow data.

File name	Description
[sensor_id].csv	Traffic flows. [sensor_id] refers to the ‘id’ from the locations.csv

Table 4-3. Data files of traffic flows.

Column name	Description
date	The date the data is collected (YYYY-MM-DD), e.g., 2021-11-04.
time	The hours of the day the data is collected range from 0 to 23, 0 = [0,1), 23 = [23,24).
flow	Number of vehicles that pass the sensor location during the one-hour interval.

Table 4-4. Description of traffic flow data attributes.

Year	2019	2022	2023
Date	10/17/2019 to 11/19/2019	04/09/2022, 04/10/2022	04/23/2023, 07/13/2023 to 07/25/2023

Table 4-5. Missing dates of data from all sensors.

4.5 Technical Validation

This section aims to validate our dataset’s quality and technical reliability through various methods. First, we analysed the spatial distribution of original and filtered sensors. Second, we analysed the temporal distribution of traffic flows during the whole study period. Third, we compared the daily average traffic flow with the stringency index across different stages of the COVID-19 pandemic, providing insights into the consistency of variation between traffic flows and external factors influencing traffic behaviours. To further ensure data reliability and integrity, we examined daily traffic flow patterns and the frequency of zero values in our traffic flow dataset. These evaluations comprehensively understand the reliability and usefulness of traffic flow datasets.

4.5.1 Spatial distribution of sensors

In this study, we apply the chi-square test to evaluate the distribution of sensors across different land cover and road type categories. The chi-square test is a statistical method used to determine whether there is a statistically significant difference between the expected and observed frequencies in one or more categories of a contingency table. For each categorical variable, land cover and road types, we constructed a contingency table (Table 4-6) that records the frequency of each category within the sensor groups, including original sensors, filtered sensors and removed high-zero sensors. The chi-square test statistic is calculated using the formula (Franke et al., 2012):

$$\chi^2 = \sum \frac{(O - E)^2}{E} \tag{4-1}$$

Where O represents the observed frequency of each category, which is the number of sensors in each land cover and road type for filtered sensors or removed high-zero sensors. E is the expected number of sensors in each land cover and road type derived from original sensors. The χ^2 statistic is used to test whether there is a statistically significant spatial distribution difference between two groups of sensors at different categories of land cover and road types. The p-value of the chi-square test comparing filtered sensors with original sensors is 0.94794, which is higher than 0.05 and very close to 1. This high p-value indicates no statistically significant difference between the distributions of the original and filtered sensors at different land cover and road types, suggesting the spatial distributions of filtered sensors are similar to those of original sensors. We also compared the distribution of removed high-zero sensors with that of the original sensors. The resulting p-value is 0.82873, which is also greater than 0.05, indicating no statistically significant difference between the distributions of the removed sensors and the original sensors across land cover and road type categories. The result suggests that sensors removed due to high-zero values are not concentrated in specific road types or land use categories. Therefore, the filtering process is unlikely to remove valuable spatial information, and the remaining filtered sensors can still be considered a good representative sample of the original sensors.

Data	Category	Original Sensors	Filtered Sensors	High-zero Sensors (removed)
Land Use (Urban Atlas, 2018)	Construction Sites	1	1	0
	Continuous Urban Fabric (S.L.: > 80%)	34	18	14
	Discontinuous Dense Urban Fabric (S.L.: 50% - 80%)	66	41	16
	Discontinuous Medium Density Urban Fabric (S.L.: 30% - 50%)	2	1	1
	Fast Transit Roads and Associated Land	21	6	15
	Forests	2	0	1
	Green Urban Areas	20	10	7
	Industrial, Commercial, Public, Military and Private Units	106	54	47
	Other Roads and Associated Land	707	336	335
	Railways and Associated Land	7	3	3
	Sports and Leisure Facilities	3	0	2
	Water	2	0	2
Road Types (OS MasterMap Highways Network, 2019)	A Road	346	168	156
	A Road Primary	52	28	22
	B Road	85	47	37
	Local Access Road	3	1	2
	Local Road	122	53	61
	Minor Road	338	163	152
	Motorway	17	5	12
	Restricted Local Access Road	6	5	0
	Restricted Secondary Access Road	2	0	1

Table 4-6. Frequency distribution of road types and land use categories for original, filtered and removed high-zero sensors.

4.5.2 Temporal distribution of daily traffic flows

Figure 4-6 shows the mean and median value of daily traffic flows over 470 sensors in Glasgow, with missing dates (Table 4-5) highlighted in grey. During the four years, the daily traffic flows consistently decreased dramatically in late December due to Christmas and rebounded to the level of average days at the beginning of January. However, the outbreak of the COVID-19 pandemic and social distancing measures restricted human mobility in the UK (Hadjidemetriou et al., 2020; Sarim et al., 2021). Following the first country-wide lockdown imposed on March 23rd, 2020 (Franke et al., 2012), there was a sharp decline in daily traffic flows across Glasgow. There was a gradual increase in traffic flows with the easing of restrictions, but it did not reach pre-lockdown levels. In January 2021, the UK government introduced a second lockdown, similar to it in March 2020 (Hale et al., 2021). This lockdown started following the Christmas period, slowing down the anticipated traffic recovery from holidays in Glasgow. The annual fluctuations of Christmas and the responses to emergency and government policies demonstrate the reliability and consistency of our traffic flow dataset.

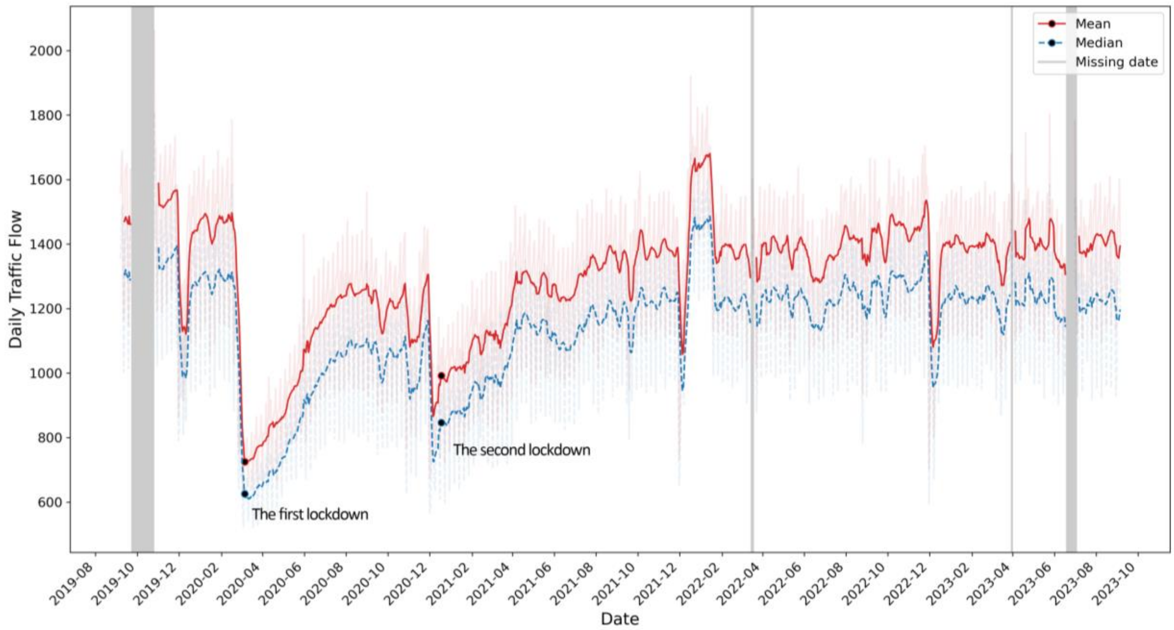

Figure 4-6. Daily traffic flows from October 1st, 2019, to September 30th, 2023.

4.5.3 Comparison with Stringency Index

The Stringency Index is a metric used to quantify the restrictions on mobility in response to the COVID-19 pandemic. The restrictions on mobility are evaluated by the Oxford COVID-19 Government Response Tracker (OxCGRT) (Aaron et al., 2020). The OxCGRT records the government responses through 21 indicators representing different policy measures. Specifically, eight indicators measure containment and closure policies, such as school and workplace closures. Another eight indicators measure healthcare responses, including facial coverings and vaccination policies. The remaining four indicators reflect economic policies, such as income support and fiscal measures, with another miscellaneous indicator. The Stringency Index is calculated as an average of the eight containment and closure indicators and one healthcare indicator, quantifying the strictness of policies that primarily restrict people's behaviour (Hale et al., 2021; Sarim et al., 2021). The Stringency Index ranges from 0 (no restrictions) to 100 (most stringent restrictions). To better compare traffic flow patterns with the introduction of restrictions, we convert the Stringency Index into the Freedom of Association Index (Sarim et al., 2021), which is calculated as follows:

$$\text{Freedom of Association Index} = 100 - \text{Stringency Index} \tag{4-2}$$

The Freedom of Association Index reflects the degree of freedom individuals have to associate and gather socially, providing a complementary perspective to the Stringency Index. Figure 4-7 illustrates a positive relationship between daily traffic flows and the Freedom of Association Index. Both the mean and median traffic flows declined significantly, corresponding to reductions in the Freedom of Association Index observed in March 2020 and January 2021. Conversely, as the Freedom of Association Index increased, indicating fewer restrictions on social interactions, traffic flows demonstrated a corresponding rise. To further validate the traffic flow dataset, Pearson's correlation coefficient (Pearson, 1900, 1920; Pearson & Henrici, 1896) and Spearman's correlation coefficient (Spearman, 1904b, 1904a) were employed to assess the degree of correlation between the Freedom of Association Index and daily average traffic flows. The results (Table 4-7) indicate a high consistency and strong correlation between the two datasets, confirming the validity and reliability of the traffic flow dataset in Glasgow.

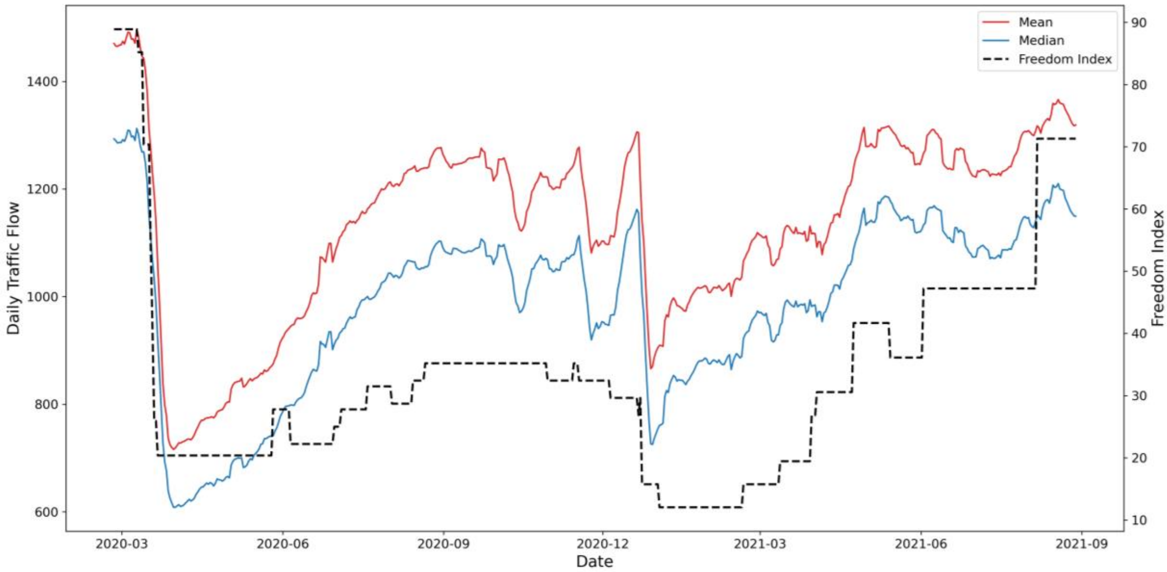

Figure 4-7. Daily traffic flows and freedom of association from March 1st, 2020, to August 31st, 2021.

	Coefficient	P value
Pearson	0.751	5.134e-101
Spearman	0.861	2.326e-163

Table 4-7. Correlation coefficients between the Freedom of Association index and daily average traffic flows.

4.5.4 Hourly traffic flows and zero frequency

Figure 4-8 demonstrates the statistical distribution of hourly traffic flows in Glasgow over 24 hours through four consecutive years. The hourly data demonstrates a consistent pattern of increasing traffic flows from morning, starting as early as 6 AM. The traffic flows continued to rise steadily, indicating sustained high demand throughout the daytime until 4 PM. From 5 PM onwards, there was a significant decrease in hourly traffic flows, reaching its lowest point at 3 AM the following day. The hourly zero frequency shows the opposite trend in Figure 4-4, where the highest frequency of zero traffic flow was observed at 3 AM. Conversely, the minimal instances of zero traffic flow were recorded from 7 AM to 10 PM. The correlation coefficient values in Table 4-8 further validate this relationship. Pearson and Spearman’s coefficients are lower than -0.8, indicating a strong negative correlation between hourly traffic flows and zero frequency. Therefore, our traffic flow data reliably captures the fluctuations in traffic throughout the day.

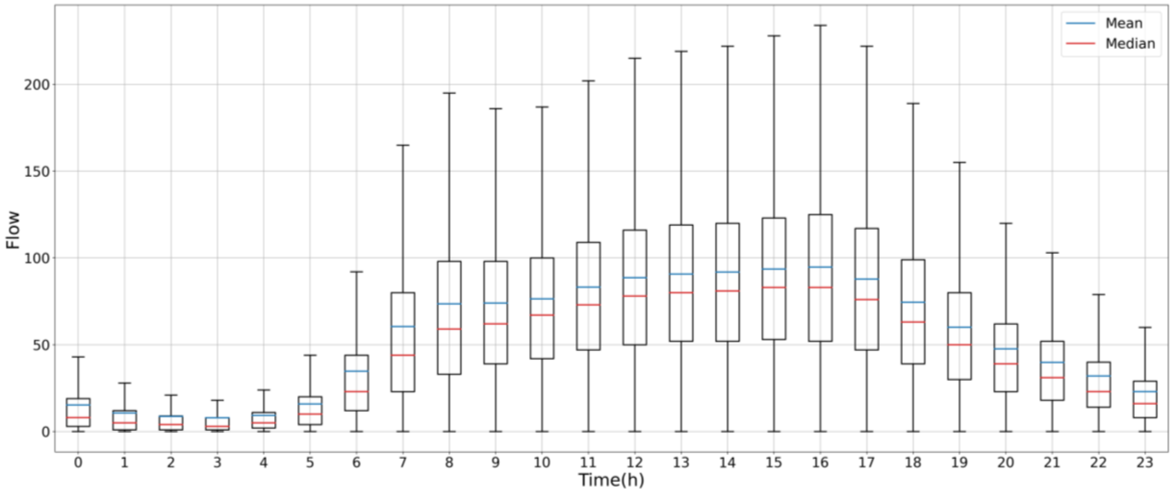

Figure 4-8. Boxplot of hourly traffic flows.

	Coefficient	P value
Pearson	-0.803	2.306e-06
Spearman	-0.908	9.133e-10

Table 4-8. Correlation coefficients between zero frequency and hourly average traffic flows.

4.5.5 Morning peak comparison

Figure 4-9 shows hourly traffic flows for 24-hour periods in different years. We compare the mean and median traffic flows during the morning rush from 8 AM to 9 AM. It can be seen that there was a minor peak during the morning rush hours in Figure 4-9(1). However, the morning peak gradually disappeared in Figure 4-9(2)-(3). That might be because, during COVID-19, many people started working from home, reducing the need for commuting during traditional rush hours (van der Drift et al., 2022). This trend highlights the significant impact of the pandemic on daily travel patterns and commuting behaviours (Aloi et al., 2020). In Figure 4-9(4), the morning peak began to reappear as restrictions eased and people returned to their workplaces. However, the post-pandemic morning peak did not return to its pre-pandemic levels. The pandemic has brought about lasting changes in work patterns, with many companies adopting hybrid or fully remote work models. This shift could lead to a long-term reduction in morning peak traffic, even after the pandemic.

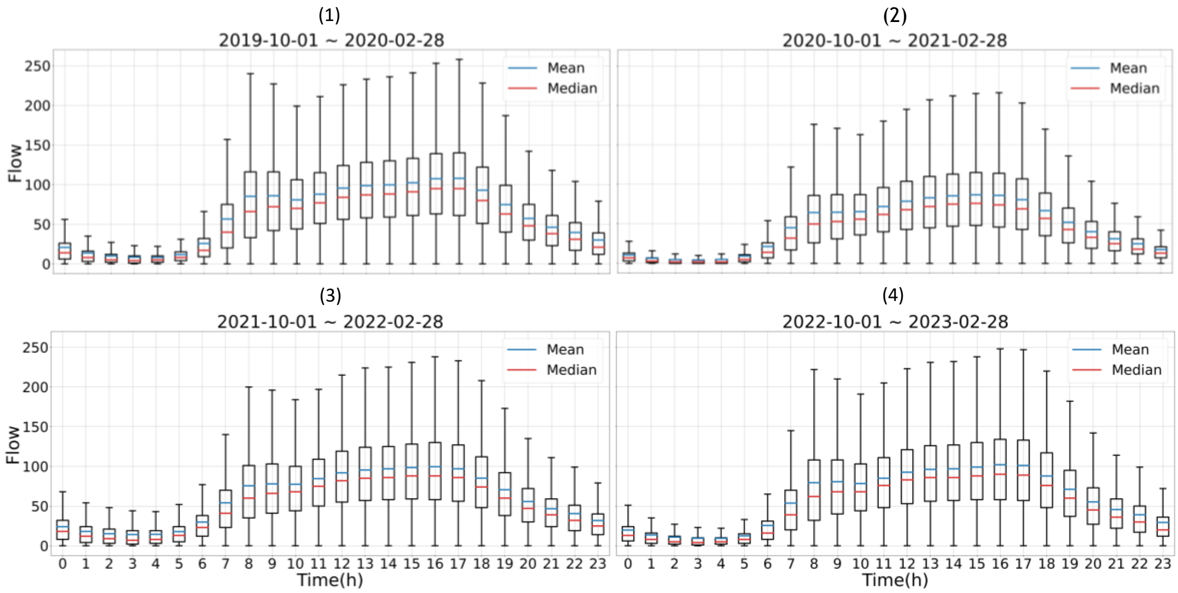

Figure 4-9. Boxplot of hourly traffic flows for four separate years.

4.6 Usage Notes

As briefly mentioned in the ‘Background & Summary’ section, this dataset can be used in various aspects. Since it is long-term traffic flow data with hourly intervals, it can be used for traffic dynamic analysis across multiple time scales, including identifying short-term peak-hour trends, long-term seasonal variations, and annual patterns. Those features can be coupled to official weather observations (Met Office, 2025), which are recorded at the same temporal scale. By combining the hourly weather observations with traffic flows, users can make long/short-term traffic flow predictions. The temporal analysis can be done using various statistical software, such as R or Python programming languages or SPSS.

This intra-city scale traffic flow data can be coupled to the surrounding built environment for spatial analysis. Some examples are the road network data and Points of Interest available from the EDINA Digimap Service platform (OS MasterMap Highways Network, 2019; Points of Interest, 2021) or land use data (Urban Atlas, 2018). Moreover, this dataset can be applied to assess the environmental impact of traffic flows, such as the variation of air quality (Department for Environment, 2025) of established low-emission zones in Glasgow (Glasgow City Council, 2025a). The spatial relationship can be analysed with Network Analyst or Buffer tools using conventional geographic information (GIS) software, such as ArcGIS, QGIS or packages for spatial data analysis for R or Python programming languages, such as rgeos, igraph, and GeoPandas.

4.7 Chapter Summary

A multi-step data cleaning and filtering process was applied to raw traffic flow records collected from the Glasgow open data portal, using spatial, temporal, and numerical filtering criteria to remove poor-quality sensor data and ensure the reliability of the final dataset. The cleaned dataset was then validated through temporal and spatial analyses, including comparisons with government policy stringency measures during the COVID-19 pandemic. This chapter contributes to the transport geography and urban mobility literature by providing a transparent and reproducible workflow for constructing and validating high-resolution intra-city traffic flow datasets from sensor data. The empirical findings demonstrate that systematic data cleaning based on multiple filtering criteria substantially improves dataset quality compared to raw sensor records, and that validation against external policy measures provides a robust basis for assessing dataset reliability.

Chapter 5 Understanding the relationship between urban influential factors and traffic flows in response to COVID-19 pandemic[2]

This chapter aims to explore the quantitative relationships between urban traffic flows and the physical, social, and environmental characteristics of neighbourhoods in Glasgow across four stages of the COVID-19 pandemic. Specifically, spatial econometric models are applied to analyse how road characteristics, socio-demographics, land use patterns, POIs, and GSV imagery influence the spatial distribution of traffic flows before, during, and after the pandemic. The high-resolution traffic flow dataset constructed in Chapter 4 provides the empirical basis for this analysis. The work presented in this chapter reveals the heterogeneous and spatially dependent nature of these relationships and provides evidence on how urban physical and social characteristics influence the traffic impacts of pandemic-period policy interventions.

5.1 Introduction

As a crucial component of the complex urban system, urban traffic analysis has drawn the attention of researchers and planners for decades (Batty, 2008). Meanwhile, the increasing development of Intelligent Transportation Systems with various urban sensing technologies (Buch et al., 2011) has produced a variety of traffic-related data to monitor urban traffic conditions in high spatiotemporal resolution. Many of the studies applied mobile device data (Y. Jiang et al., 2021; Kupfer et al., 2021), smart card data (Mützel & Scheiner, 2022; Y. Zhou, Liu, et al., 2021), and road detector data (Y. Gao & Levinson, 2022; Z. Liu & Stern, 2021), to explore the spatial and temporal evolution of human mobility patterns in both pre- and COVID-19 period. However, they mostly only explored the pandemic's impact, with limited aspects considered for the built environment and socio-demographics. Those existing studies overlooked the integrated influence of COVID-19 and other surrounding environments on urban traffic flows.

Numerous research studies have examined the effects of the COVID-19 pandemic on travel behaviours and patterns by leveraging traffic flow data (Aloi et al., 2020; Y. Gao & Levinson, 2022; Z. Liu & Stern, 2021; Parr et al., 2020; X. Tian et al., 2021). This new

[2] Li, Y., Zhao, Q., & Wang, M. (2024). Understanding urban traffic flows in response to COVID-19 pandemic with emerging urban big data in Glasgow. Cities, 154, 105381. https://doi.org/10.1016/j.cities.2024.105381

form of data, primarily acquired through road detectors and cameras embedded in Intelligent Transportation Systems, has been extensively utilised. However, most investigations focused on analysing changes in traffic flows during a limited time, typically spanning a few months (Aloi et al., 2020; Parr et al., 2020; X. Tian et al., 2021). Only limited studies have employed traffic flow data collected over several years (Y. Gao & Levinson, 2022; Z. Liu & Stern, 2021). Regrettably, the post-COVID-19 changes in traffic flows have been largely overlooked. In this chapter, we aim to address this gap by utilising comprehensive time series traffic flow data to examine the dynamics of traffic flows before, during, and after the COVID-19 pandemic.

The overarching goal of this research is to understand the quantitative relationship between the urban physical and social elements (i.e., built environment, socio-demographics) and traffic dynamics by using new forms of urban big data and spatial econometric model in Glasgow. The contribution of this chapter is threefold. First, it bridges the research gap between the topics of COVID-19 mobility patterns and influential factors of urban traffic flows by exploring the heterogeneous and linear relationship between the influential urban factors and traffic flows by different COVID-19 stages. Second, it applies the long time series traffic flow data spanning multiple years in Glasgow, which has been sparsely investigated in previous research conducted in the United Kingdom. It also conducts a detailed comparative analysis of traffic flow changes at a high temporal granularity, delineated into four distinct stages: 'Before COVID-19', '1st lockdown', '2nd lockdown', and 'Post COVID-19'. Third, it highlights the distance-sensitive heterogeneous effects of the green space on urban traffic flows by applying Google Street View images as the emerging urban big data. It also reveals the patterns of spatial dependence on traffic flows and urban factors at different stages of the COVID-19 pandemic. The research outputs will help city planners and policymakers understand what physical and social factors will influence the traffic flows for urban planning and resource allocation. It is valuable in data-driven governmental decision-making and helps enhance community responses to the future pandemic.

5.2 Background

5.2.1 Influential factors of urban traffic flows

As a crucial component of the complex urban system, urban traffic analysis has drawn the attention of researchers and planners for decades (Batty, 2008). Numerous studies have been conducted on the impact of urban factors on traffic dynamics, which can be summarised as the socio-demographics and built environment factors. Several studies have investigated the influence of socio-demographics on daily travel behaviours in cities via quantitative analysis using survey datasets with information such as age, race, gender, income, and educational level (J. Ma et al., 2014; Schoenau & Müller, 2017; M. Wang & Mu, 2018; Y. Zhou, Yuan, et al., 2021). Existing research found that residents with higher incomes, better employment, and more children are more likely to travel by car (Klinger & Lanzendorf, 2016). Limited research has investigated how socio-demographics influence sensor-measured urban traffic flows. In addition to socio-demographics, numerous studies have explored the influence of the urban built environment on urban traffic flows. With the built environment, road characteristics are the most concerning and important factors in early traffic flow research (N. He & Zhao, 2013; Irawan et al., 2010). Recent research found that the longer the road and the lower frequency of the intersections are conducive to city motor vehicles (Cubells et al., 2023; Yokoo & Levinson, 2019).

In recent years, the development of sensing technologies and crowdsourcing platforms have produced a variety of urban big data (Y. Pan et al., 2016), including land use data from satellite imagery, Point of Interest (POI) from OpenStreetMap, and street-level images from street level vehicle scanning. POI is the precise positioning of urban function points (Nian et al., 2020; Z. Xu et al., 2019), which has been proven to have a strong correlation with travel behaviours (J. Bao et al., 2015; Gong et al., 2016; R. Jiang et al., 2021; Y. Yue et al., 2017). Specifically, areas with entertainment and consumption functions are more likely to generate more traffic flows (Nian et al., 2020; Z. Xu et al., 2019). However, the attraction of consumption POIs on travel behaviour significantly decreased, while the impact on residential areas increased during the pandemic (Nian et al., 2020). Urban land use typically refers to the land surface modified by human activities in urban areas (Ellis, 2013; Q. Liu et al., 2021). Similar to POIs, several studies connect land use with urban travel behaviours (Bandeira et al., 2011; Y. Jiang et al., 2021; M. Lee & Holme, 2015; Q. Liu et al., 2021; M. Wang & Debbage, 2021). Most focus on traffic prediction via land use (Bandeira et al., 2011; M. Lee & Holme, 2015), and some inferred urban land use from human mobility data (Q. Liu et al., 2021; G. Pan et al., 2013). Street-level imagery is a novel source of large-scale urban data that provides panoramic information along the streets (Goel et al., 2018; Ibrahim et al., 2020). Google Street View (GSV) is one of the most common sources of street imagery, widely used to identify human mobility patterns in cities (Bartzokas-Tsiompras et al., 2021; Goel et al., 2018; M. Wang et al., 2022). Although the urban built environment has been used to explore its influences on urban traffic flows, few studies explore the quantitative relationship between POIs, land use, GSV, and traffic flows in cities. This research fills the gap in the urban environment from a quantitative analysis perspective using emerging urban big data.

5.2.2 Spatial models on urban traffic analytics

Regression analysis is a statistical technique for modelling and investigating the relationships between a dependent variable and one or more independent variables (Montgomery, 2015). Linear regression has been widely used in various transportation research, analysing the relationship between human travel behaviours and various urban factors (road characteristics, socio-demographics, surrounding built environments, etc.) (Boarnet et al., 2008; Ozbil et al., 2011, 2019; Vance & Iovanna, 2007; X. Xu et al., 2017).

Although linear regression has been widely used to understand the relationships between urban traffic flows and associated influential factors, the explanation of the generation of urban traffic flows via linear regression models is limited due to the neglect of potential spatial dependence in different locations (Koenig, 1999; Haworth, 2018). For instance, the traffic flows of two adjacency road links are more similar than two unconnected roads. The spatial dependence can be quantified using spatial autocorrelation indices from the spatial regression models, which incorporate the spatial correlation into the traditional regression framework. Various researchers have applied spatial regression models to capture the spatial autocorrelation between the urban environment and traffic behaviour. Wang et al. (2020) compared the performance of the spatial error model (SEM), spatial autoregressive model (SAM), and spatial Durbin model (SDM) on the relationship between Uber accessibility and road network structure. The results show that SDM is favoured over SAM, and SEM reveals the worst performance. Rhee et al. (2016) identified that the performance of the SEM was better than the SAM in quantifying the traffic crash frequency with road length and speed limit, while the geographically weighted regression model provided valuable insights about localisation effects. Considering the spatial features of urban traffic behaviour, the spatial regression model has been implemented to measure pedestrian behaviours' demographic and urban environmental relationships (Ha & Thill, 2011; LaScala et al., 2000). The social, economic, and transportation hubs were considered spatial variables that impact freight traffic generation (Novak et al., 2011), while weather events affected the spatial distribution of freight truck flows (Akter et al., 2020).

5.3 Study area and data

Glasgow (Figure 5-1) is the most populous city and has the largest economy in Scotland (BBC News, 2017; Statista, 2019). Glasgow is the focal point of Scotland's road network, with tens of thousands of residents commuting daily to the city (Department for Transport, 2023). Cars are Glasgow's most popular mode of transport, and two-thirds of people use them for journeys around the city (Scotland's Census, 2022). Table 5-2 explains the data sources for this chapter, including traffic flow data, urban land use data, socio-demographic data, POI data, road characteristics data, and the GSV images in Glasgow.

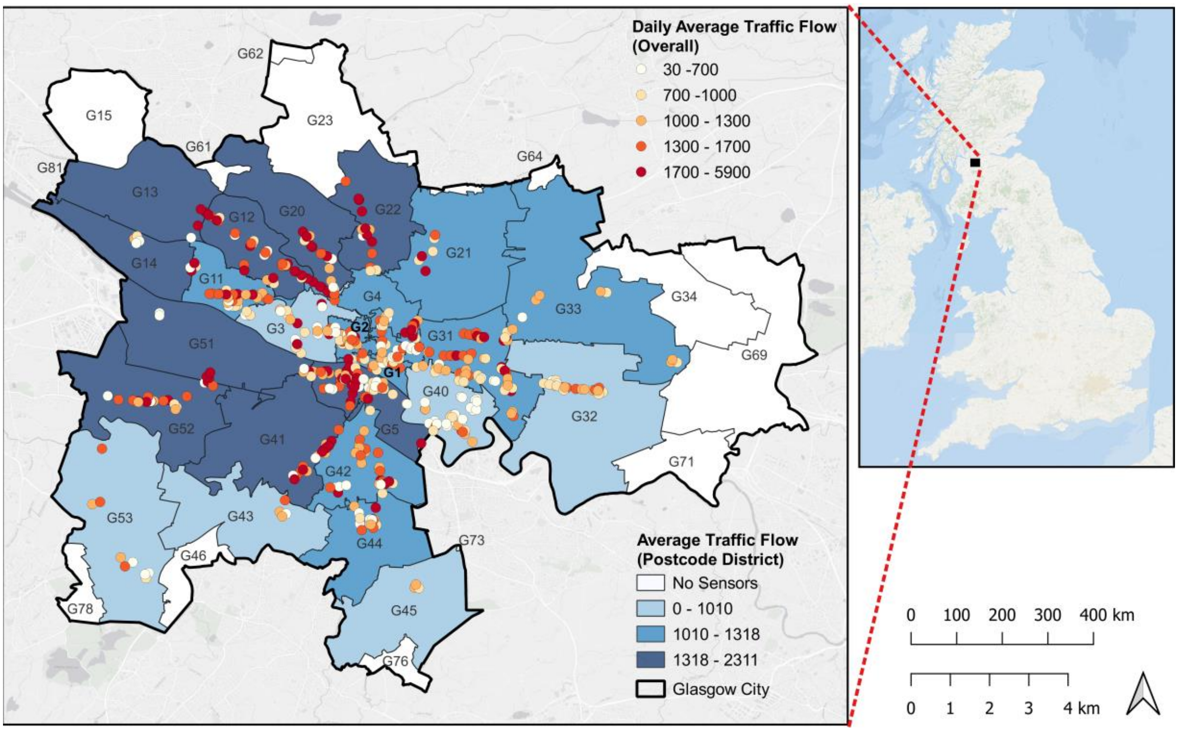

Figure 5-1. The spatial distribution of average daily traffic flows from August 9, 2019, to October 16, 2021, in Glasgow.

5.3.1 Urban traffic flows

This study collects traffic flow data from August 9, 2019, to October 16, 2021, by road detectors within Glasgow City. The road detectors include various above- and below-ground traffic sensors to record the traffic flows at specific points. The traffic sensors only collect the number of motor vehicles, which cannot discriminate the vehicle type. We group the traffic data into four stages based on COVID-19 lockdown periods published by the Scottish government and available dates of traffic data (Hale et al., 2021; Institute for Government, 2021), including traffic flows 'Before COVID-19' from August 9, 2019, to

October 16, 2019, '1st Lockdown' from March 24, 2020, to May 28, 2020, '2nd Lockdown' from January 6, 2021, to March 13, 2021, and 'Post COVID-19' from August 9, 2021, to October 16, 2021. Both lockdown periods are under the C6 level of OxCGRT Indicators, which refers to the policy of Stay-at-home Requirements (Hale et al., 2021). During the study period, 1033 sites of traffic flows were recorded, from which 530 valid sites have been used in this research, located from the main road (motorway) to the fifth-class road (local road), with a time interval of 15 minutes.

The workflow of the data cleaning process is listed in Figure 4-1 by filtering the traffic flow data with spatial and temporal constraints (Y. Li et al., 2025). Since automatic traffic sensors collect raw traffic flow data, inspecting and cleaning the data before any analysis is necessary. Therefore, we extracted the coordinates of each recorded site and compared them to the geographic location of the GCC area. Sites not within this area are beyond the scope of the research and not considered in the next step (59 sites). The second step tries to filter the traffic data on the temporal scale. The study period in this research is from August 9, 2019, to October 16, 2021, 800 days overall. The records of 69 sites in Glasgow start later than August 2019 or end before October 2021. The third step of the cleaning process focuses on the record and error percentage of the real-time data. GCC has applied an interpolation method for traffic flows when no data is returned. 48 of 905 remaining sites in Glasgow are detected and removed with more than 18% interpolated data, with the rest fewer than 1%. The fourth step considers the spatial relationship between the traffic flows and the road network. Since sensors record the traffic flows in Glasgow along the road, the range of the Euclidean distance between each site and the nearest should be considered. In Glasgow, more than 99% of detectors are located within 15 meters of roads. Only 9 sites are 20 meters farther away, so we have removed them from our analysis. Lastly, after performing all the above spatial and temporal inspections, we can filter the traffic flow data numerically.

Consecutive zero value is the most frequent data issue in the time series study. In this research, the consecutive zero value refers to no vehicles passing the road for hours or days. First, we remove the 189 sites with records showing more than 90% zero traffic flow during the study period. Then, the recorded dates with more than 24 hours of consecutive zero are eliminated for each recorded site, assuming that at least one motor vehicle should be passing by for daily routine in Glasgow urban areas. Recorded dates without traffic flow for more than one day are incorrect and are not considered in this study. 530 of 659 remaining sites are selected, with the most recorded dates remaining showing 754 of 800 days. Overall, we filtered out 530 records after the data-cleaning process and calculated the daily traffic flows for each site. Consequently, Figure 5-2 demonstrates the spatial variation of the daily average traffic flows across four COVID-19 stages.

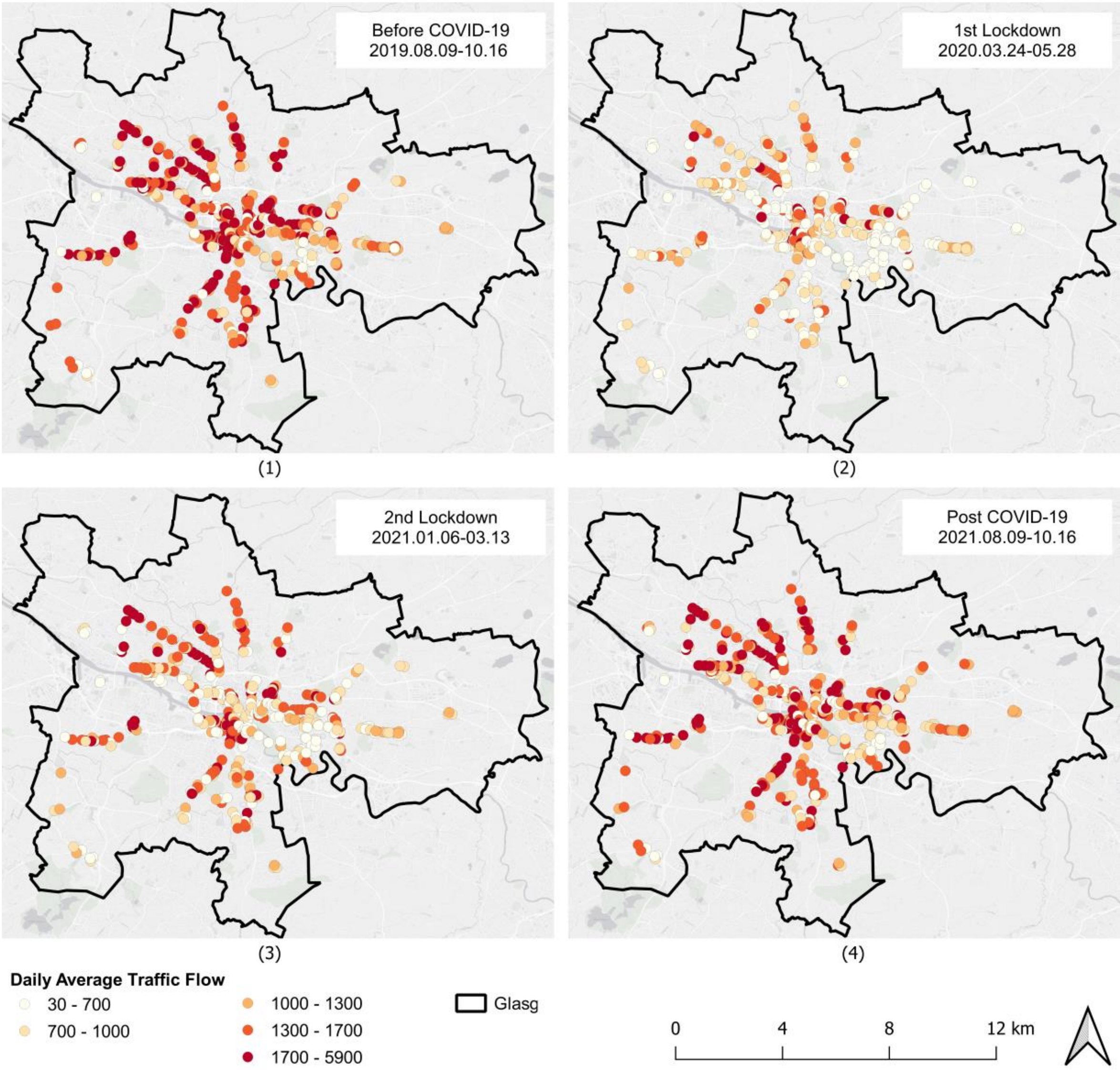

Figure 5-2. The spatial distribution of traffic flows in four COVID-19 periods in Glasgow.

5.3.2 Distribution of traffic flows

In this research, we aggregate the raw traffic flows daily. By employing this data, we compute the average daily traffic flows for each recorded site, aiming to understand the spatial correlation between traffic flows and the built environment. A visualisation of the statistical distribution of average daily traffic flows in Glasgow over different periods is shown in Figure 5-3. During the regular period without the pandemic, the average daily traffic flows are approximately 1,460 among each recorded site. Due to the outbreak of COVID-19 and the first lockdown in March 2020, the average traffic flow slumped to 788.

Compared to the period before COVID-19, the total daily average traffic flows recorded by 530 detectors during the first lockdown is 417,250, which is only 56.8% of daily traffic flows in a regular period. The phenomenon was relieved during the second lockdown, with the average daily traffic flow rising to around 1,024, showing a 30% recovery from the first lockdown period. During the post-COVID-19 period, the average daily traffic flows grew to 1334 in Glasgow. Although the daily traffic flows kept increasing after the end of the first lockdown, there is still approximately a 10% difference in the daily average traffic flows during the post-pandemic period to the regular before October 2019.

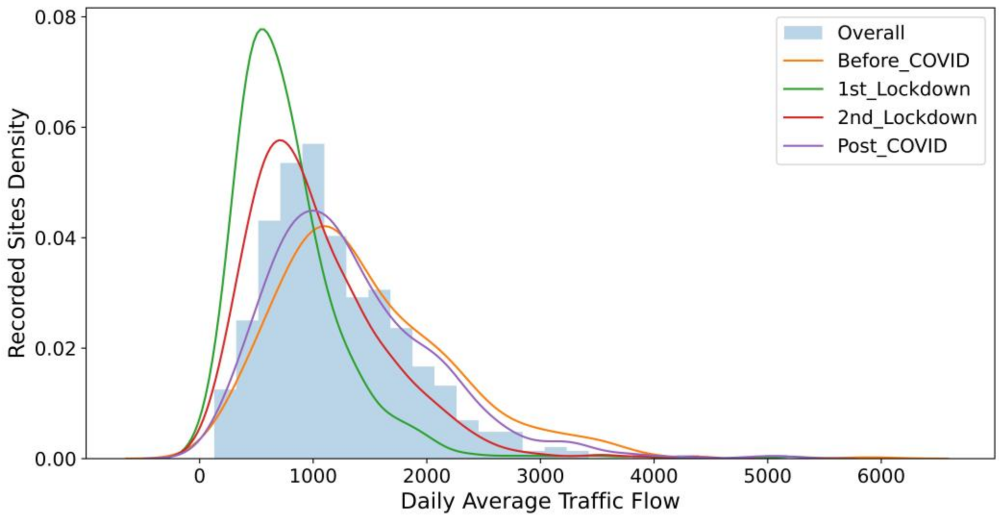

Figure 5-3. Histogram of daily average traffic flows.

The spatial distribution of daily average traffic flows throughout the study period is shown in Figure 5-1. It can be observed from the map that there is considerable variation in the average daily traffic flow across Glasgow. A spatially West-East divide pattern can be observed on the map. The number of motor vehicles travelling in the western part of Glasgow is generally higher than those in the east. In the eastern part of Glasgow, the daily traffic flows are higher towards the city centre and lower in peripheral areas. However, relatively low traffic flows are observed in the G3 and G40 area. This could be attributed to the fact that the G3 area is largely residential, encompassing many local flats and student accommodations. Furthermore, Kelvingrove Park, a substantial green space within the G3 area, may also contribute to the low traffic flows. Similar to G3 area, G40 area is a suburban district in Glasgow characterised by several residential neighbourhoods and the historical Glasgow Green Park, leading to the low traffic flows. In the south of Glasgow, the G53, G43, and G45 areas demonstrate low traffic flows, due to their predominantly residential areas and large scale of green space, such as Cathkin Braes Country Park and Pollok Country Park.

We also compare the spatial distribution of traffic flow across four pandemic stages. Figures 5-2(1) and 5-2(2) show that the spatial distribution of daily average traffic flows during the first lockdown and the regular period changed dramatically. Table 5-1 shows a noticeable reduction in the daily average traffic flows during the first lockdown compared to the period before COVID-19, nearly halving across most areas of Glasgow. Table 5-1 further reveals that during the second lockdown, there was an increase in daily traffic flows across nearly all areas of Glasgow compared to the first lockdown, except for the G2 area. This phenomenon could be attributed to the 'City Centre Interventions' implemented by the Glasgow City Council in the second half of 2020, such as road closures, which consequently restricted vehicular accessibility within the G2 area. Both Figure 5-2(4) and Table 5-1 indicate that in most areas of Glasgow, the number of motor vehicles travelling each day almost rebounds to the level of the regular period when the government lifted the restriction.

Zone	1st Lockdown compare to pre COVID-19 (%)	2nd Lockdown compare to pre COVID-19 (%)	2nd Lockdown compare to 1st Lockdown (%)	Post COVID-19 compare to pre COVID-19 (%)
G1	-44.7	-38.4	17.5	-6.6
G11	-46.9	-33.2	31.1	-6.0
G12	-48.7	-25.4	57.7	-11.0
G13	-49.2	-22.8	56.0	5.2
G14	-48.3	-28.4	43.0	-11.3
G2	-30.4	-39.6	-8.3	-15.9
G20	-50.1	-23.3	59.1	0.1
G21	-43.1	-24.0	33.2	-9.1
G22	-43.0	-21.7	39.1	-4.1
G3	-49.2	-38.1	32.4	-13.3
G31	-46.3	-28.9	39.8	-11.9
G32	-27.5	-23.6	8.2	-6.8
G33	-45.1	-21.4	45.9	-0.4
G4	-47.6	-37.8	26.5	-16.5
G40	-48.7	-30.5	38.8	-8.4
G41	-52.2	-27.8	55.1	2.1
G42	-49.0	-25.9	50.6	-6.0
G43	-55.0	-31.1	54.8	-14.3
G44	-49.7	-24.0	53.9	-8.0
G45	-34.7	-8.1	40.6	13.1
G5	-46.2	-30.6	38.0	-9.2
G51	-37.2	-21.0	31.1	0.3
G52	-49.0	-28.9	42.7	-1.0
G53	-40.5	-23.6	31.0	-3.4

Table 5-1. Comparison of traffic flows between different COVID-19 stages and the period before COVID-19.

5.3.3 Independent variables

Independent variables considered in this research include land use, socio-demographics, Point of Interest, Google Street Views, and road characteristics. The land use dataset provides information on Functional Urban Areas in Glasgow in 2018. There are 27 types of Functional Urban Areas across the GCC area. Based on their functionality and the syndromes of human activities, we aggregate them into six groups (Figure 5-4): urban residential areas; green urban areas; natural areas; industrial, commercial, public, military, and private units; roads and railways; and others. The satellite image classification is at 10 metres resolution by using Sentinel-2 data. The socio-demographic information is provided by the 2011 Scottish Census at the Output Area (OA) level (Scotland's Census, 2021). Across the GCC area, there are 5,486 OAs, for which we collect key socio-demographic indicators, including population characteristics (total population, gender composition, population density), age structure (median age and age-group proportions), ethnic composition (area-level percentages of major ethnic groups), and educational attainment (proportion of residents with degree-level qualifications). Following previous studies (Ma et al., 2014; Schoenau and Müller, 2017; Yang Zhou et al., 2021), the variables selected and calculated for modelling include median age, percentage of male residents, percentage of White residents, and percentage of residents with a college-level qualification (2011 Census, 2013). We get 28,703 POIs from the Digimap in Glasgow and the Ordnance Survey, categorising them into seven groups: retail; accommodation, eating and drinking; attractions; sports and entertainment; transport; education and health; and public infrastructure. Road network data from Digimap provides details of road types, names, lengths, and widths. We use the information on road types (Figure 5-4) and length to measure the road characteristics of the nearby traffic flows. GSV is a new and novel source that provides a more intuitive and human-perspective street view to understand the built environment of the cities (M. Sun et al., 2022). We obtain the GSV images from the Street View Static Application Programming Interface (API), and images of each site are recorded from 4 perspectives: 0°, 90°, 180°, and 270° (Figure 5-5). The latest updated images are selected for analysis, with dates no earlier than 2019. We apply the pre-trained DeepLab model from TensorFlow to perform semantic segmentation on GSV images (H. Yu et al., 2020). The outputs demonstrate the pixel percentage of 19 typical cityscape objects, from which the most relevant categories, such as roads, buildings, vegetation, and cars, are considered in this study.

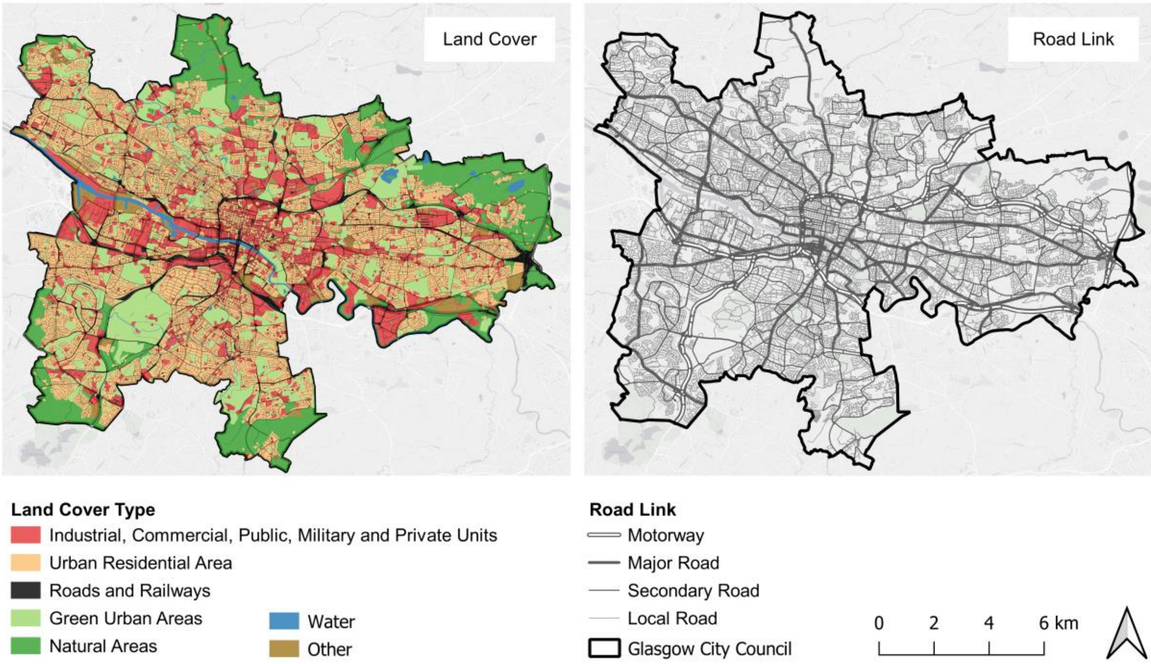

Figure 5-4. Spatial distribution of land cover types and road links in Glasgow.

To align the spatial resolution of the independent variables, we create buffer zones from each traffic sensor and calculate the percentage or density of each variable within the buffer area (Figure 5-5). For example, the density of road link represents the total length of roads per unit area within the buffer zone; the percentage of land use type is weighted by the share of each spatial area within the buffer area; and the percentage of POI is calculated via the number of each POI category divided by the total number of POI within the buffer zone. We calculate the percentage of socio-demographic data in two steps. First, the census Output Area located near the recorded sites is partly segmented into the buffer zone. We calculate the socio-demographics (including the total population) of each segmentation area separately by weighting the segmented area within the Output Area ($q_{ij} = OA_{ij} \times w_i j$). Then, we add the socio-demographics of each segmentation area together and divide them by the total population of the buffer zone to get the percentage of socio-demographics ($P_j = \sum_i \frac{q_{ij}}{q_{i,pop}}$). Concerning the Modifiable Area Unit Problem (MAUP), we test different buffer radii varying from 100 m to 400 m with a step of 100 m. The detailed comparison between buffer sizes is presented in the results section. Variable selection is also performed to avoid the multi-collinearity problem. We calculated the variance inflation factor (VIF), and VIFs greater than five were excluded from the analysis (Akinwande et al., 2015). All the variables used in this study are aggregated at 200-meter buffer within the sensor location and therefore represent area characteristics rather than individual behaviours or attributes. Table 5-2 summarises the descriptive statistics for all variables (VIF $\leqslant$ 5) with a 200-meter buffer.

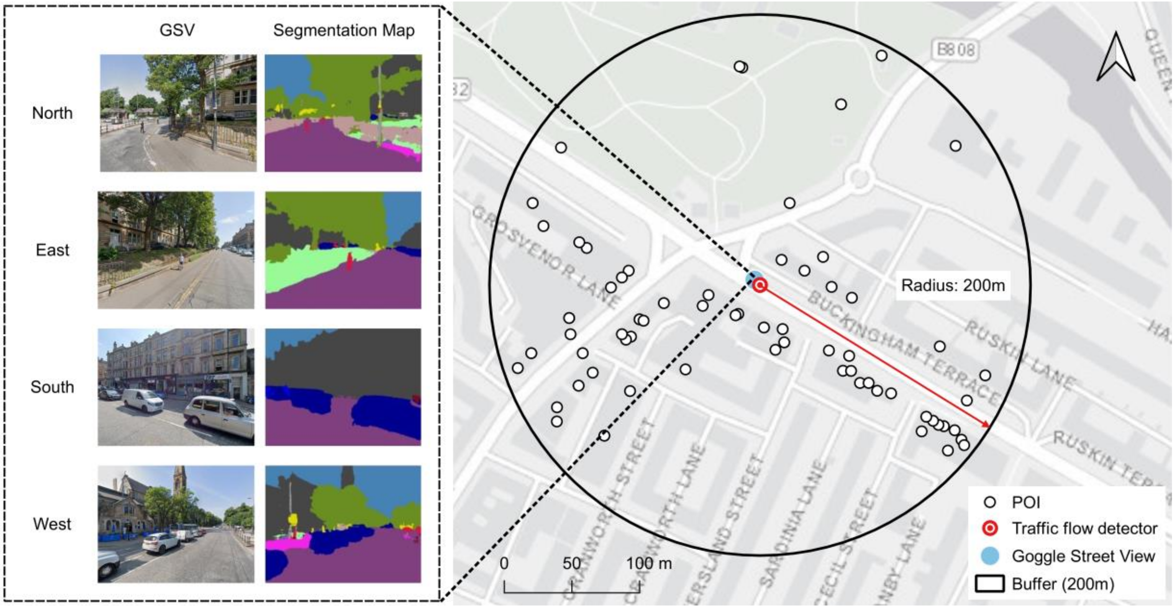

Figure 5-5. Spatial distribution of GSV and POIs within traffic sensor buffer (200m).

Variable	Data source	Category	Mean	Std. dev	Min	Max
Dependent variable						
Average daily traffic flows	Glasgow City Council (GCC) (GCC, 2022)	Before COVID-19	1459.223	803.606	43.710	5901.232
		1st Lockdown	787.265	513.501	35.154	5197.569
		2nd Lockdown	1024.469	601.138	66.938	4362.308
		Post COVID-19	1333.983	733.496	139.029	5145.044
Independent variable						
Road link	EDINA Digimap Service (OS MasterMap Highways Network, 2019)	Motorway (km/sq.km)	0.700	2.639	0.000	19.165
		Major road (km/sq.km)	4.109	3.443	0.000	16.576
		Secondary road (km/sq.km)	4.195	2.995	0.000	14.309
		Local road (km/sq.km)	12.714	5.050	1.516	26.756
POI	EDINA Digimap Service (Points of Interest, 2021)	Quantity	72.987	82.868	4.000	586.000
		Public Infrastructure (%)	0.157	0.106	0.000	0.875
		Education and health (%)	0.066	0.056	0.000	0.333
		Transport (%)	0.154	0.137	0.000	0.882
		Retail (%)	0.126	0.100	0.000	0.600
		Sport and entertainment (%)	0.042	0.050	0.000	0.353
		Accommodation, eating, and drinking (%)	0.113	0.084	0.000	0.500
		Attractions (%)	0.024	0.047	0.000	0.444
Land use	Urban Atlas (Urban Atlas, 2018)	Industrial, commercial, public, military, and private units (%)	0.311	0.211	0.000	0.961
		Roads and railways (%)	0.181	0.084	0.028	0.475
		Urban residential areas (%)	0.389	0.231	0.000	0.857
		Natural areas (Water included) (%)	0.014	0.046	0.000	0.307
		Green urban areas (%)	0.094	0.118	0.000	0.691
		Other (%)	0.010	0.046	0.000	0.538
Socio-demographic	National Records of Scotland (NRS) (Scotland's Census, 2011)	White (%)	0.857	0.089	0.538	0.992
		Mean age	37.525	5.424	22.797	59.562
		Male (%)	0.511	0.060	0.394	0.797
		College degree (%)	0.280	0.161	0.034	0.627
GSV	Google Maps Platform (Google Developers, 2022)	Road (%)	0.293	0.050	0.123	0.423
		Building (%)	0.208	0.167	0.000	0.583
		Vegetation (%)	0.126	0.119	0.000	0.553
		Car (%)	0.036	0.037	0.000	0.201

Table 5-2. Summary statistics of variables (with a 200-metre buffer).

5.4 Methodology

This section provides a detailed description of our methodology, and the steps for model selection are: (1) Conduct the linear regression analysis; (2) Construct the spatial weight matrix; (3) Perform the global Moran's I test and Lagrange Multiplier test for linear regression residuals; (4) Employ the spatial econometric models with spatial weight matrix.

5.4.1 Spatial weight matrix

To measure the spatial dependence of urban traffic flows, it is necessary to construct the geographic relationship of each recorded site. The spatial weight matrix can represent the magnitude of the spatial relationships based on the locations of the traffic flows and those of their neighbours (Rey et al., 2020; M. Wang et al., 2020). The general expression of the spatial weight matrix is shown below (Nian et al., 2020):

$$W = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nm} \end{pmatrix} \tag{5-1}$$

The n × m spatial weight matrix quantifies the spatial correlation between different recorded sites, and w_{ij} represents the degree of spatial correlation between the recorded site i and the neighbours j (Gelb, 2022). In this study, we construct the spatial weight matrix based on the k-nearest neighbours (k-NN) algorithm. K-NN defines that the traffic flows of the recorded site *i* is influenced by the nearest k observations of traffic flows. Therefore, for spatial autocorrelation between the traffic flows, the spatial weight matrix is denoted as:

$$W_{ij} = \begin{cases} 1, & if\ d_{ij} \leq d_{ik} \\ 0, & if\ d_{ij} > d_{ik} \end{cases} \tag{5-2}$$

Where d_{ij} indicates the Euclidean distance between site *i* and site *j*, d_{ik} represents the Euclidean distance between site *i* and the farthest site k among the k-nearest neighbours.

5.4.2 Spatial econometric models

As mentioned in the literature review, spatial dependence has been widely considered in the research of urban travel behaviours. Therefore, the spatial autocorrelation analysis should be performed in the model selection procedure to evaluate whether there is a relationship between daily average traffic flows and geographical locations. In this study, we conduct three spatial econometric models to analyse the association between urban parameters and average daily traffic flows in Glasgow (Anselin et al., 2013). We will start with a brief introduction of the linear regression model, which extends to the spatial econometric models. According to Montgomery et al. (2012), a linear regression model can be defined as:

$$Y = X\beta + \varepsilon \tag{5-3}$$

Where Y is a vector of the dependent variable, X is a matrix of independent variables. β presents the vector of the regression coefficients, and ε is the vector of random errors. The linear regression model assumes that the errors and dependent variables are uncorrelated.

According to LeSage and Pace (2010), a spatial error model (SEM) assumes the error terms across different spatial units are correlated, which violates the assumption of uncorrelated error terms in a linear regression model. A spatial autoregressive model (SAM) assumes autocorrelation is present in the dependent variables. The spatial Durbin model (SDM) is a SAM that assumes autocorrelation may be present in one or more independent variables and the dependent variable.

The basic form of an SEM is:

$$Y = X\beta + \mu \tag{5-4}$$

$$\mu = \lambda W\mu + \varepsilon \tag{5-5}$$

The basic form of a SAM is:

$$Y = \rho WY + X\beta + \varepsilon \tag{5-6}$$

The basic form of an SDM is:

$$Y = \rho WY + X\beta + WX\theta + \varepsilon \tag{5-7}$$

Where W is the spatial weight matrix derived by the k-NN method. $W\mu$ is the correlated interaction effects, referring to those similar urban environmental characteristics hidden between adjacent neighbourhoods, which can affect traffic flows according to similar approaches with the coefficient λ (M. Wang et al., 2020). WY describes the spatial interaction between adjacent neighbourhoods that appears among the traffic flows Y with a spatial lag coefficient ρ, also named endogenous interaction effects (Elhorst, 2014). WX represents the exogenous interaction effects, which are the spatial interaction effects (the spillover effects of a spatial model) on the urban parameters X among adjacent neighbourhoods with a spatial autoregressive coefficient θ.

In the selection procedure of models, global Moran's I is a measure to quantify the spatial autocorrelation in traffic flow residuals of linear regression. The formula can be defined as follows (Draper & Smith, 1998):

$$I = \frac{n}{S}\frac{\epsilon^T W \epsilon}{\epsilon^T \epsilon} \tag{5-8}$$

The drawback of global Moran's *I* is that it does not reveal the type of spatial autocorrelation. The Lagrange Multiplier (LM) test is designed to test which type of spatial regression model is most appropriate for the traffic flow data. The expression of the LM test for SEM is:

$$LM_{Error} = \left(\frac{n\epsilon' W y}{\epsilon' \epsilon}\right)^2 [tr(W'W + W^2)]^{-I} \tag{5-9}$$

Where *n* is the number of observations of traffic flows, *S* is the sum of spatial weights in *W*, ϵ is the residual error obtained by OLS estimation of the linear regression model. $\hat{\beta}$ refers to the estimated parameters of a linear regression model, *I* is the value of Moran's *I*, and *tr* is the matrix trace operator.

In addition, the Akaike information criterion (AIC) was used in the model selection. The AIC is a mathematical method that can be used to evaluate the relative quality of a collection of models for a given set of data (McElreath, 2018; Stoica & Selen, 2004; Taddy, 2019). Specifically, AIC compares the performance of different models and determines which models best fit the dataset (Zajic, 2019). The AIC value of the model is the following:

$$AIC = 2k - 2\,ln(\hat{L}) \tag{5-10}$$

Where k is the number of estimated parameters in the model, $\hat{L}$ is the maximised value of the likelihood function of the model. In statistics, AIC calculates the relative amount of information lost by a given model. Therefore, the best-fit model, according to AIC, is the one that generates the highest quality and loses the least information (Bevans, 2020).

5.5 Results

Before applying the model selection method proposed by Anselin et al. (2013), we first select the model from the theoretical perspective. The traffic flows from geographically close roads are often more similar than those from more widely separated road links. Besides, the urban parameters, such as the type of land use, POI, and socio-demographics, are highly likely to be located near similar parameters. For example, the cinema is always situated around the shopping centre, both places of recreation and people from the same ethnic group prefer to dwell in the adjacent neighbourhoods. Considering the potential endogenous and exogenous spatial interaction effects mentioned above, the SDM is preferred. Then, we follow the standard procedures of model selection. An OLS-based linear regression analysis is conducted on the relationship between daily average traffic flows and the urban characteristics within four different buffer sizes. To meet the assumption of a normal distribution from the linear regression model, we apply the log transformation on the daily average traffic flows and all the independent variables in percentage.

5.5.1 Results of global Moran's I and Lagrange Multiplier test

By substituting the spatial weight matrix based on the nearest neighbours into the OLS regression, the statistical results of the global Moran's I test are obtained to test the spatial dependence of models. We calculate the global Moran's I for the Ordinary Least Squares residuals of daily average traffic flows during four pandemic stages. Figure 5-6 presents the distribution of global Moran's I value and the corresponding P-value for different combinations of buffer size and k-NN. All the P-values are lower than 0.05, suggesting the existence of spatial autocorrelation. Therefore, spatial econometric models are preferred to avoid biased estimations via OLS.

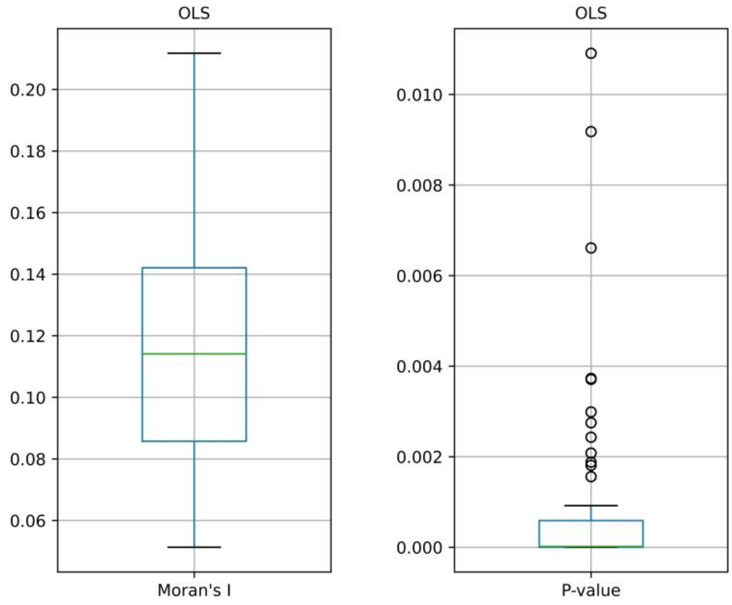

Figure 5-6. Boxplot of global Moran's I test on OLS residuals (64 models).

Figure 5-7 presents the results of Lagrange multiplier diagnostics among four periods for different combinations of buffer size and four spatial weight matrices based on k-NN. The buffer size ranges from 100 metres to 400 metres, with a 100-metre step. The LM diagnostics includes four estimates of tests (Anselin, 2005; M. Wang et al., 2020): the standard LM test for the error dependence (LM-Error), the standard LM test for an unobserved spatially lagged dependent variable (LM-Lag), the robust LM test for the error dependence based on the possible presence of an unobserved lagged dependent variable (RLM-Error), and the robust LM test for an unobserved spatially lagged dependent variable based on the possible presence of error dependence (RLM-Lag). Only to conduct the robust versions of the LM diagnostics when the standard versions are significant ($p < 0.05$). According to Figure 5-7, both the LM-Error and LM-Lag statistics are highly significant, with the latter slightly more so. In this case, further efforts are required by considering the robust forms of diagnostics. Here, only the p-value of RLM-Lag statistics is all less than 0.05. Although some results of RLM-Error are significant here, the p-value of RLM-Lag is much lower than that of RLM-Error, which indicates the preferred models between SAM and SDM (Anselin, 2005). Furthermore, the values of both log-likelihood and Pseudo-R2 in Figure 5-8 indicate that the SDM is favoured over SAM. Therefore, this study focuses on the results provided by SDM.

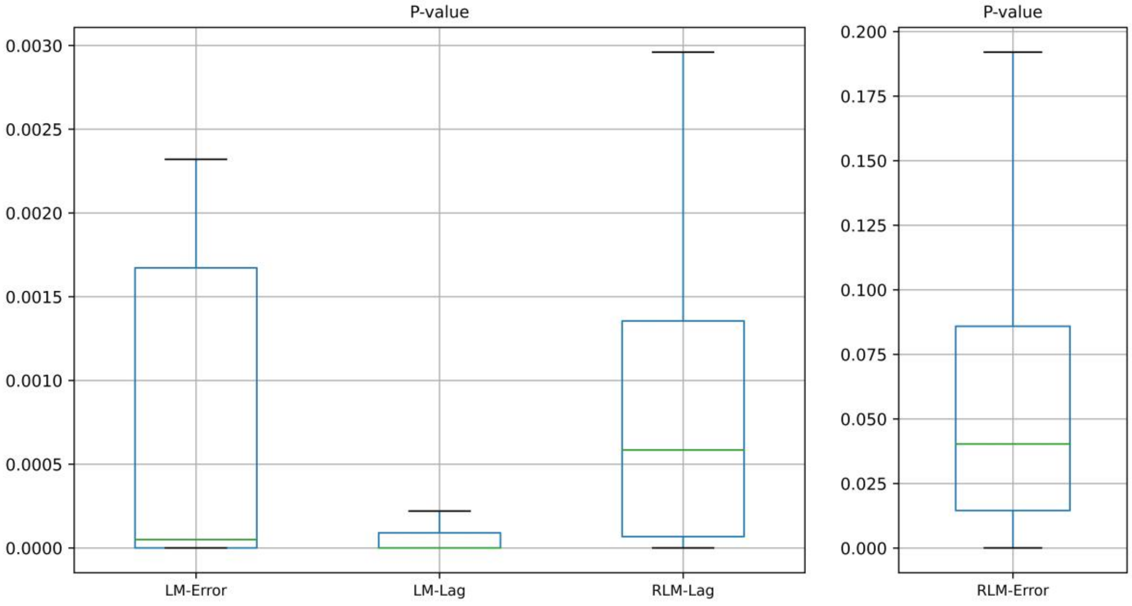

Figure 5-7. Boxplot of P value from Lagrange multiplier (LM) diagnostics.

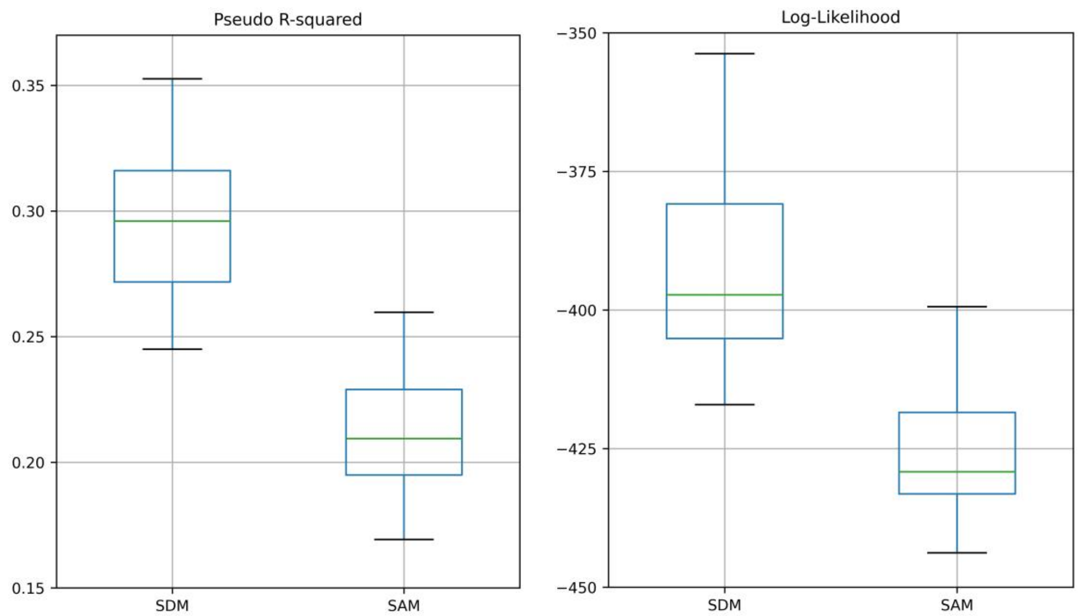

Figure 5-8. Boxplot of two model parameters - Pseudo R-squared and Log-Likelihood.

5.5.2 Results of spatial econometric models

With the 200 meters buffer from the traffic sensors and the four nearest neighbours[3] of the spatial weight matrix, we quantitate the relationship between traffic flows, urban infrastructure, and socio-demographic indicators at four pandemic stages in Glasgow. According to the results of the RLM-Lag test in Table 5-3, we detect that the spatial dependence between adjacent neighbourhoods among the traffic flows and urban parameters is variable during the four COVID-19 periods. The statistic value of RLM-Lag drops from 17.754 to 10.299 at the first two stages, demonstrating that the spatial dependence becomes weak due to the pandemic outbreak. However, the statistic value rises to 23.185 in the second lockdown, suggesting the magnitude of spatial dependence during the second lockdown becomes more substantial than before. Besides, both the values of RLM-Lag and AIC (Table 5-4) reveal that all the variables after COVID-19 show the most substantial spatial dependence.

	Before COVID-19		1st Lockdown		2nd Lockdown		Post COVID-19	
	Stat.	P	Stat.	P	Stat.	P	Stat.	P
LM-Error	7.756	0.005	9.327	0.002	30.531	<0.001	16.980	<0.001
LM-Lag	15.905	<0.001	15.601	<0.001	46.174	<0.001	31.304	<0.001
RLM-Error	9.605	0.002	4.026	0.045	7.541	0.006	14.653	0.001
RLM-Lag	17.754	<0.001	10.299	0.001	23.185	<0.001	28.977	<0.001

Table 5-3. Results of Lagrange multiplier (LM) diagnostics.

	Before COVID-19			1st Lockdown			2nd Lockdown			Post COVID-19		
	SDM	SAM	SEM	**SDM**	SAM	SEM	**SDM**	SAM	SEM	**SDM**	SAM	SEM
Log-Likelihood	-412.046	-425.466	-425.697	-415.382	-434.369	-435.908	-401.066	-412.415	-422.124	-378.388	-397.935	-398.933
Pseudo-R^2	0.252	0.216	0.194	0.250	0.198	0.175	0.305	0.256	0.192	0.277	0.229	0.177
AIC	956.092	918.933	917.394	962.764	936.738	937.816	934.133	910.831	910.248	888.776	863.871	863.866

Table 5-4. Results of model parameters.

Table 5-5 presents the significant results of SDM between urban parameters and daily average traffic flows. We can observe minor differences in the significance of the estimated coefficients during the four pandemic periods. The density of major roads is significantly positively related to the daily average traffic flows before and during the

[3] Due to the limited space, a detailed selection of spatial weight matrix and buffer size can be found in Appendices

lockdown but changes to insignificant after COVID-19. In this study, the major road refers to the type that intends to provide principal and large-scale transport links within or between cities and towns (Ordnance Survey, 2021). The insignificant result of traffic flows between distanced destinations supports the idea that people have reduced their long-distance travel after the COVID-19 lockdown. This could be due to the increased adoption of remote work, online shopping, and virtual social activities, which reduces the necessity for physical travel. Furthermore, from the cityscape objects extracted from GSV, we observe that the relationship between the percentage of vegetation covered along the roads and the number of vehicles passing by was only significant before the pandemic. Comparing the different significant levels of two vegetation-related characteristics (Pct. of natural areas (land use) and Pct. of vegetation (from GSV)), we identify that the green space within the surrounding area has a significant impact on urban traffic flows while those in the immediate nearby location are insignificant after the breakout of COVID-19.

From the regression coefficients of urban characteristics from the SDM, a negative relationship exists between the natural areas and the daily average traffic flows, indicating that fewer vehicles travel to the natural green spaces than the other areas. The mean age of residents in Glasgow ranges from 23 to 60, and the areas with more young and white dwellers are associated with more traffic flows. The phenomenon may result from most youngsters living in areas with high population density, like the city centre, which attracts many motor vehicles. Furthermore, the major roads connected between and within cities and towns always have heavy traffic flows before and during COVID-19. The values of the regression coefficients remain stable among the four stages, indicating the consistency of the model results.

Y=Log(flows)	Before COVID-19		1st Lockdown		2nd Lockdown		Post COVID-19	
	Beta	P	Beta	P	Beta	P	Beta	P
(Intercept)	6.751 ***	0.000	5.939 ***	0.000	5.416 ***	0.000	5.938 ***	0.000
Log(Pct. of Natural areas)	-0.061 **	0.009	-0.088 ***	0.000	-0.065 **	0.004	-0.053 *	0.015
Mean age	-0.027 *	0.038	-0.031 *	0.019	-0.031 *	0.015	-0.036 **	0.003
Log(Pct. of White)	1.325 *	0.031	1.264 *	0.040	1.540 *	0.010	1.602 **	0.003
Major Road (km/sq.km)	0.037 *	0.044	0.038 *	0.039	0.039 *	0.027	0.031	0.062
Log(Pct. of Vegetation)	-0.039 *	0.036	-0.017	0.358	-0.010	0.569	-0.022	0.207

*, **, and *** indicate significance at the 0.05, 0.01, and 0.001 levels, respectively.

Table 5-5. Results of the relationship between urban parameters and daily average traffic flows of SDM.

5.6 Discussions

In this chapter, we extend previous work by exploring the relationship between urban parameters and traffic flows across the COVID-19 pandemic in Glasgow. Specifically, it provides knowledge of how the built environment and socio-demographics matter in the daily average traffic flows, compensating the previous study that considers the pandemic outbreak as the sole impact of travel behaviours (Aloi et al., 2020; Bucsky, 2020; Hadjidemetriou et al., 2020; Parr et al., 2020). Second, we employ the long time series traffic flow data spanning multiple years in Glasgow. In the United Kingdom, limited research has utilised this emerging form of data due to its inherent challenges, characterised by disorganisation, incompleteness, and errors. This can be attributed to the automated collection of data from road detectors. In this research, we construct a detailed data clean process for raw traffic counts from traffic sensors, which support reproducibility, replicability, and extensibility to other study areas.

Additionally, our study conducts a detailed comparative analysis of traffic flow changes at a high temporal granularity, delineated into four distinct stages: 'Before COVID-19', '1st Lockdown', '2nd Lockdown', and 'Post COVID-19'. This approach stands in contrast to prior research, which only focused on comparing traffic flow differences between the pre-pandemic and during-pandemic periods (Aloi et al., 2020; Y. Gao & Levinson, 2022; Z. Liu & Stern, 2021; Parr et al., 2020; X. Tian et al., 2021). Third, by leveraging the emerging urban big data source of Google Street View images, our study highlights the heterogeneous effects of green space on urban traffic flow, specifically emphasising its sensitivity to distance variations. It also identifies how different stages of COVID-19 contribute to the spatial dependence of traffic flow and urban parameters. The research outputs will help city planners understand what physical and social factors will influence the traffic flows for urban planning and resource allocation.

We have found that the areas with more young and white dwellers show higher traffic flows, while areas covered with natural green space show lower traffic flows. This is not surprising as youngsters may prefer to live in the busy city centre for leisure activities and easy access to different amenities, and areas with a higher percentage of white residents tend to coincide with major roads and well-connected neighbourhoods, which is associated with higher observed traffic flows. Major roads between cities and towns also show heavier traffic flows as tens of thousands of residents commute daily to Glasgow (Department for Transport, 2023). These findings inform where cities should prioritise investing in the public transport infrastructure and promoting active travel. Besides, the impact of land cover types like natural areas decreases due to COVID-19. We also detect that the spatial dependence between adjacent neighbourhoods among the traffic flows and urban parameters increases significantly after the pandemic. The results are consistence with previous research that the travel demand is more linked to community life after COVID-19 (Nian et al., 2020). Unlike other studies, we have a new finding with novel data source Google Street View images that the heterogeneous effects of the green space on the urban traffic flows, as the magnitudes of their effects vary by distance. We identify that green space within a surrounding area has a more significant impact on urban traffic flows than those in the immediate nearby location, which makes it easy to understand that car travelling is distance-oriented rather than attracted by the environment at a single location.

In summary, this research bridges the gap between the literature on quantitative analysis of urban built environments and the understanding of influential factors affecting urban traffic flows. By examining the time series of traffic data encompassing four distinct stages of the COVID-19 pandemic, we explore the heterogeneous and linear relationship between these influential urban factors and traffic flow patterns. This research provides a comprehensive analysis integrating COVID-19 mobility pattern literature insights with the broader context of urban traffic flows. The outputs will offer valuable insights to city planners and policymakers regarding the physical and social factors influencing traffic flows, which can inform effective urban planning and resource allocation strategies. Specifically, these insights can help to support and enhance government policies such as Glasgow's Low Emission Zone (Glasgow City Council, 2018), which is in place on June 1, 2023. This knowledge can inform the design and implementation of targeted interventions within the Low Emission Zone, including optimising traffic management systems, promoting alternative modes of transportation, and strategically locating infrastructure to mitigate congestion and pollution. The integration of long-term traffic flow data and analysis of multiple years' worth of data from Glasgow further strengthens the reliability and robustness of the research findings, ensuring their applicability to real-world policy decisions.

Several limitations exist in this study, which could also pave the path for future work. First, we mix all the types of motor vehicles in the traffic flow analysis, such as private cars and public transport. Ideally, information considering the differences in traffic flows between public and private transport will provide a more comprehensive view of the traffic analysis for COVID-19. In the future, we plan to extend the current work to active travel with further data support, for example, how the traffic flows of cyclists and pedestrians change during COVID-19 compared to motor vehicles. Second, traffic sensors are unevenly distributed across the GCC area, with many located in neighbourhoods that have a high proportion of White residents (mean White% > 0.85). This spatial bias likely contributes to the observed association between higher traffic flows and areas with more white residents. All socio-demographic variables are aggregated within a 200-metre buffer, representing area characteristics rather than individual behaviours. Therefore, these correlations do not imply that specific demographic groups driving more or less. Instead, they reflect broader relationships between traffic flows, urban built environment, and neighbourhood characteristics. As a result, the findings should be interpreted as area-level associations rather than evidence of causal effects attributable to specific demographic groups. Future research could incorporate individual-level mobility or travel behaviour data to better identify and understand potential causal mechanisms. Third, we focus on the spatial impact of variables on the average daily traffic flows in four different periods and overlook the temporal variation of traffic flows. Future work can conduct the time-series analysis, including the traffic flow changes under different weather conditions during the day, weekdays vs. weekends, holidays, and seasons. We also intend to undertake a temporal analysis of traffic flows to scrutinise and comprehend patterns during peak periods. Besides, we can use our current analysis framework to evaluate the usefulness of implementing the new transport policy. The newly established low-emission zone was operated on June 1, 2023. We can evaluate the traffic flow changes within and outside the low-emission zone and estimate the new policy's effectiveness.

5.7 Chapter Summary

Understanding urban traffic flows in high spatiotemporal resolution has been an immediate agenda for creating net-zero carbon cities. Taking the city of Glasgow as an example, we have found that not only the socio-demographics, such as the age and ethnic group of people, are associated with traffic flows, but also the land cover types, such as green space and major roads are related to the traffic flows. Meanwhile, the heterogeneous effects of green space on urban traffic flows exist, as the magnitudes of their effects vary by distance. Furthermore, we have explored the variation of spatial dependence between adjacent neighbourhoods among the traffic flows and the urban parameters in response to COVID-

19. With the influence of COVID-19, there has been a significant decrease in long-distance travel. The noticeable change in travel behaviour presents a valuable opportunity to encourage active travel and achieve a net-zero carbon target in the near future (Calafiore et al., 2022).

This chapter adds to the literature by demonstrating how multi-source urban indicators can be integrated within spatial econometric frameworks to reveal the heterogeneous and spatially dependent determinants of urban traffic flows. The findings show that the relationships between traffic flows and urban characteristics are not static but vary in response to changing mobility conditions. The chapter also provides empirical evidence on how urban physical and social characteristics influence the traffic impacts of pandemic-period policy interventions across different stages of restriction. These insights can inform urban planners and policymakers in developing spatially targeted, data-driven strategies for transport planning, resource allocation, and community resilience in response to future public health emergencies.

Chapter 6 Zero-Shot Traffic Flow Prediction with Foundation Models: A Comparison with Deep Learning Approaches

This chapter aims to evaluate and compare the performance of deep learning models and emerging time series foundation models in forecasting urban traffic flows under both normal conditions and disruptive events. Specifically, two pre-trained foundation models are applied for zero-shot traffic flow prediction, and their accuracy is compared against three deep learning models using the long-term Glasgow traffic flow dataset constructed in Chapter 4. Multiple context lengths and model sizes are tested to analyse the sensitivity, generalisation, and computational efficiency of each model. The work presented in this chapter provides a systematic empirical comparison of machine learning and time series forecasting models in a real-world, multi-year urban traffic context. It also demonstrates the practical application of zero-shot foundation model prediction for adaptive and resilient traffic management under both normal and disruptive conditions, with implications for smart cities and intelligent transport systems.

6.1 Introduction

Traffic flow prediction is a critical task of intelligent transportation systems (ITS) (Y. Liu, Rasouli, et al., 2024; X. Yin et al., 2022), focusing on predicting future traffic flow conditions based on historical and real-time data (H. Chen & Rakha, 2014; G. Guo & Yuan, 2020; Y. Kim et al., 2024; C. Liu, Yang, et al., 2024). Accurate traffic prediction plays a crucial role in urban planning, infrastructure management, and traffic control, which helps to reduce traffic congestion, enhance road safety, and lower environmental impacts (J. Chen et al., 2024; Fan et al., 2024; Y. Kim et al., 2024; Y. Li et al., 2024). Due to the rapid growth of urban populations and vehicle ownership worldwide, cities face increasing challenges to maintain smooth traffic flow (Kalašová & Stacho, 2006). Effective prediction of traffic flows provides transportation authorities, city planners, and travellers with timely information that enables better decision-making, more efficient resource allocation, and an improved quality of life (Y. Liu, Rasouli, et al., 2024; Ren et al., 2024; Sattarzadeh et al., 2025).

Traffic flow prediction is fundamentally challenging because traffic flow is not only a mechanical time series but emerges from the aggregation of individual travel decisions (Cascetta, 2009) influenced by factors such as route preferences, departure time choices, and mode selections. Discrete choice models have demonstrated that travellers make decisions based on utility maximisation (McFadden, 1974b), responding dynamically to traffic conditions, time of day, and external events (M. E. Ben-Akiva & Lerman, 1985). This behavioural foundation means that traffic patterns reflect both systematic regularities in activity schedules and adaptive responses to changing traffic conditions, creating non-stationary and non-linear temporal dynamics that are difficult to model using traditional parametric models (Cascetta & Cantarella, 1991; Ortúzar & Willumsen, 2011a). While these behavioural models provide theoretical insight into the mechanisms generating traffic flows, their implementation for real-time prediction faces practical challenges due to the difficulty of estimating numerous behavioural parameters and computational complexity in large-scale networks (Cascetta & Cantarella, 1991). This gap between behavioural understanding and operational prediction capability motivates the exploration of data-driven methods that can capture the complex patterns resulting from aggregate travel behaviour without requiring explicit behavioural specification.

The traffic flow prediction models have evolved from traditional statistical approaches to deep learning models in recent years (C. Liu, Yang, et al., 2024). Initially, statistical models such as Autoregressive Integrated Moving Average (ARIMA) dominated the field due to their simplicity, interpretability (Y. Zhang et al., 2023), and effectiveness in modelling linear (Y. Wang et al., 2022) and stationary time-series data. However, these models often struggled to capture complex, non-linear relationships in real-world traffic conditions (Kashyap et al., 2022). To overcome these limitations, deep learning models have been applied broadly, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks and more recently, Transformer-based architectures (Kashyap et al., 2022; Y. Kim et al., 2024; Y. Li, Chai, et al., 2021; Y. Liu, Rasouli, et al., 2024; Méndez et al., 2023; Zhou et al., 2021). CNNs are good at capturing local temporal patterns in traffic data by applying convolution operations along the time dimension (Y. Li, Li, et al., 2021), while LSTMs are effective in modelling long-term temporal dependencies because of their gated mechanisms (D. Wu et al., 2024; Z. Xia et al., 2024; Y. Zhao et al., 2024). Transformer-based models further improve on prediction accuracy by using self-attention mechanisms (Zhou et al., 2021) to capture both short- and long-term dependencies in traffic data more efficiently and flexibly. Despite their improved accuracy and adaptability to complex scenarios, deep learning models typically require extensive computational resources and large datasets for training (Ren et al., 2024), which presents challenges for practical implementation and real-time applications. Besides, these models are often developed for specific tasks (Ansari et al., 2024), which may lead to overfitting and reducing their ability to generalise effectively to new or unseen data.

In the context of government mobility interventions and large-scale disruptive events, such as COVID-19, traffic flow prediction becomes even more challenging. The imposed restrictions, such as lockdowns and social distancing measures, caused rapid changes in travel behaviour, leading to increased irregularities and deviations from historical traffic trends (Borkowski et al., 2021; Ebrahim Shaik & Ahmed, 2022; Y. Hu et al., 2023; Nouvellet et al., 2021; Parr et al., 2020; Patra et al., 2021; Warren & Skillman, 2020). Most existing traffic prediction models only trained on pre-pandemic data (C. Ma et al., 2022b; Sattarzadeh et al., 2025; Y. Zhang et al., 2023; Y. Zhao et al., 2024), which limits their ability to make accurate predictions on traffic flows during periods of significant disruption. Limited models have attempted to address this challenge by considering external factors, such as the effects of imposed response measure (Ghanim et al., 2022) and the evolving status of COVID-19 (Liapis et al., 2021). Another research involved decomposing irregular traffic flows into distinct attributes and predicting them separately to improve model performance during the pandemic (H. Li et al., 2023). However, these models often rely on the availability of extensive labelled datasets that capture the effects of mobility restrictions and event status over time, making them difficult to implement in real-time and across various regions with differing policies.

Recently, the development of Large Language Models (LLMs) has stimulated interest in developing ‘foundation models’ for time series (Ansari et al., 2024) and introduced new opportunities for traffic flow prediction (C. Liu, Yang, et al., 2024). Initially designed for natural language processing tasks, LLMs learn extensive general knowledge by pre-training on large amounts of textual data (Brown et al., 2020; H. W. Chung et al., 2022; Touvron, Lavril, et al., 2023). A distinctive strength of pre-trained LLMs is their capability for zero-shot prediction, allowing them to perform various tasks without requiring task-specific training examples (Gruver et al., 2024; H. Liu, Zhao, et al., 2024; Mirchandani et al., 2023). Models such as GPT have demonstrated impressive zero-shot performance across numerous language understanding and generation tasks from different domains (Brown et al., 2020; OpenAI et al., 2024; Radford et al., 2018, 2019). Motivated by these advances, researchers have started exploring foundation models for time series prediction (Gruver et al., 2024; H. Liu, Zhao, et al., 2024; H. Xue & Salim, 2023). By specifically pre-training existing transformer-based language model architectures on large-scale time series datasets, these models learn to capture the temporal patterns and dynamics in sequential data effectively (Ansari et al., 2024; Rasul et al., 2024). Inspired by this capability, we are motivated to apply time series foundation models to zero-shot traffic flow prediction tasks, enabling accurate forecasting of traffic conditions without the need for large amounts of task-specific datasets.

The overarching goal of this research is to present a comprehensive analysis to compare the performance of traditional deep learning models and time series foundation models for traffic flow prediction under normal conditions and disruptive events. The contribution of this chapter is threefold. First, it bridges the research gap in applying foundation models to traffic flow prediction by comparing the performance of two groups of time-series foundation models and traditional deep learning models on the SCOOT dataset (Y. Li et al., 2025). Second, it evaluates prediction accuracy on heterogeneous and unusual traffic patterns, an area that has been sparsely explored in previous research. It utilises a long-term traffic flow dataset that includes a unique global pandemic period, which allows models to capture long-term traffic trends, seasonal fluctuations, and emergency-related variations, contributing to more robust predictive performance. Third, it highlights the performance gap between time series foundation models with different model size and the diversity and temporal coverage of its training data. A well-trained foundation models with comprehensive datasets is more likely to achieve superior zero-shot performance, making it a practical and efficient choice for real-world traffic flow prediction applications. The research outputs will support city planners in integrating time-series foundation models into intelligent traffic control systems, enhancing their ability to respond effectively to both routine traffic conditions and unexpected disruptions. It is valuable in helping transportation authorities and urban policymakers make informed, data-driven decisions in traffic management for future large-scale emergencies.

6.2 Background

6.2.1 Traffic Flow Prediction

Traffic prediction aims to forecast key factors such as vehicle flow, speed, and congestion levels (Akhtar & Moridpour, 2021; Aljebreen et al., 2024, 2024; Alvi et al., 2024; C. Chen et al., 2021; Y. Jia et al., 2016, 2017; Park et al., 2011). Traffic flow prediction is one of the most fundamental and widely studied tasks in ITS. The theoretical foundations of traffic flow prediction draw from traffic flow theory, which models vehicle movement at the macroscopic level through fundamental relationships between flow, density, and speed

(Lighthill & Whitham, 1955; Richards, 1956b), and macroscopic models such as the classical Greenshields model that propose a linear relationship between traffic speed and density (Greenshields, 1934).Besides, discrete choice models and activity-based models predict traffic demand by modelling individual travel decisions and daily activity patterns (M. E. Ben-Akiva & Lerman, 1985; Bowman & Ben-Akiva, 2001b). However, these theory-driven approaches face practical limitations for real-world traffic flow prediction. Physics-based traffic flow models often rely on assumptions about driver behaviour and traffic homogeneity, which can be difficult to satisfy in complex urban environments with mixed traffic compositions, varying driver populations, and irregular network geometries (Hoogendoorn & Bovy, 2001). While activity-based models are theoretically sound, they require substantial survey data for calibration and computational resources to estimate parameters and simulate individual decisions for large populations (Castiglione et al., 2015) These limitations have motivated researchers to explore data-driven methods that can capture complex traffic patterns without requiring specification of underlying behavioural or physical mechanisms.

Traditional approaches typically rely on statistical models, such as ARIMA (Van Der Voort et al., 1996) or Kalman filter (Okutani & Stephanedes, 1984), to capture traffic patterns and seasonalities, often serving as a strong baseline when data exhibit relatively stable trends (Y. Wang et al., 2022). While these models are relatively straightforward and interpretable (Y. Zhang et al., 2023), they may struggle with irregular fluctuations in large-scale transportation networks (Kashyap et al., 2022). To address these complexities, researchers introduced machine learning models such as Random Forests (Leshem & Ritov, 2007) and Support Vector Machines (J. Tang et al., 2019). By integrating a richer set of input features, these methods can account for additional factors like weather conditions, special events, or road incidents (S. Yang & Qian, 2019). Although more flexible than purely statistical techniques, they often struggle to achieve consistently robust performance across diverse traffic scenarios.

In recent years, deep learning approaches have shown significant promise due to their capability for automatic feature extraction and handling complex dependencies. Convolutional Neural Networks (CNNs), traditionally used for image data, have been adapted for time series prediction by applying convolutional filters along the temporal dimension (Y. Li, Li, et al., 2021). This allows CNNs to extract local features, detect short-term patterns, and reduce noise in traffic data. Recurrent Neural Networks (RNNs) further enhance sequence modelling by processing time series data, capturing the dynamic behaviour of traffic flow (S. Lu et al., 2021; Y. Tian & Pan, 2015; H. Zhu et al., 2020). To overcome limitations like vanishing gradients in standard RNNs, Long Short-Term Memory (LSTM) networks, an advanced type of RNN, employ gating mechanisms to maintain long-term dependencies (C. Guo et al., 2024; J.-D. Wang & Susanto, 2023; S. Wang et al., 2020; Xiao & Yin, 2019; L. Xiong et al., 2022), making them especially effective for predicting complex temporal patterns such as rush-hour peaks or irregular traffic flows.

More recently, transformer-based models have gained attention for traffic flow prediction due to their self-attention mechanisms (Jiang et al., 2023), which enable efficient modelling of long-term temporal dependencies and global interactions without relying on recurrent structures. By capturing both short- and long-term patterns in parallel, transformers have demonstrated strong performance and scalability in large-scale traffic prediction tasks. Among these models, Informer (Zhou et al., 2021) is a representative transformer-based architecture designed for long-sequence time series forecasting, which improves computational efficiency through a probabilistic sparse self-attention mechanism while maintaining the ability to capture long-term temporal dependencies.

6.2.2 Large Language Models

Recent progress in computer hardware and the availability of large text datasets have led to the development of transformer-based LLMs that demonstrate impressive performance on various natural language processing tasks (H. W. Chung et al., 2022; Ren et al., 2024; Touvron, Martin, et al., 2023; W. X. Zhao et al., 2024). Language models are designed to predict the next token in a sequence by estimating the probability of each token based on those that have already appeared (Ansari et al., 2024). Tokens may be characters, subwords (Sennrich et al., 2016), or words from a vocabulary. The transformer architecture (Vaswani et al., 2017) was initially developed as an encoder-decoder system for machine translation (Ansari et al., 2024) and is currently applied in many popular models, such as BART (Lewis et al., 2019) and T5 (Raffel et al., 2023). In these models, the input text is first converted into a continuous representation using an encoder, after which the decoder generates output tokens sequentially based on the representation and previous tokens. Alternatively, a decoder-only architecture, used in models like GPT-3 (Brown et al., 2020) and Llama 2 (Touvron, Martin, et al., 2023), only considers tokens before the current token when making predictions. This architecture simplifies the model's design while still achieving robust performance.

LLMs are trained on extensive collections of text and can have millions to hundreds of billions of parameters (Chowdhery et al., 2022; Raffel et al., 2023). Researchers have found that increasing the number of parameters in these models leads to better performance (Brown et al., 2020). When the number of parameters becomes large enough, LLMs perform traditional language tasks more accurately and show new abilities that smaller models lack (Ren et al., 2024). Zero-shot generalisation is one such ability where the model makes predictions on tasks it was not explicitly trained for (Ansari et al., 2024). For example, Brown *et al.* (2020) demonstrated that as the number of parameters grows, LLMs acquire the skill to handle new tasks without additional, task-specific training. This connection between model parameters and zero-shot generalisation highlights that LLMs not only improve their flexibility and power in language understanding and generation but also become capable of tackling challenges such as forecasting time series data.

6.2.3 Large Language Models for Time-series Prediction

LLMs have recently developed as useful tools for time series forecasting by using their powerful sequence modelling and pattern recognition capabilities (Mirchandani et al., 2023). PromptCast (H. Xue & Salim, 2023) first treats time series forecasting as a natural language generation task, converting numerical inputs and outputs into textual prompts, thus allowing general-purpose language models to serve as core forecasting engines. However, PromptCast often requires carefully designed prompts, which can be time-consuming in complex or domain-specific scenarios. LLMTime (Gruver et al., 2024) addresses these limitations by directly tokenising time series data and treating forecasting as next-token prediction. This tokenisation strategy not only avoids extensive prompt engineering but also allows pre-trained LLMs, like GPT-3 and LLaMA, to produce robust zero-shot forecasts across a variety of benchmark datasets (Ansari et al., 2024; Gruver et al., 2024). However, LLMTime can be computationally and memory-intensive due to the large size of models, and it requires careful rescaling of data to handle varying magnitudes or precision.

6.2.4 Time Series Foundation Models

Unlike PromptCast and LLMTime repurpose large pre-trained LLMs with textual or digit-based prompts, researchers have further developed time series foundation models by training foundation models with large, diverse time series datasets. Rasul *et al.* (2024) propose a foundation model (Lag-Llama) designed explicitly for univariate time series forecasting. Built on a decoder-only transformer architecture that uses lag features as covariates, Lag-Llama is pre-trained on a broad collection of real-world time series across multiple domains including energy, transportation, economics, environmental science, air quality and cloud operations. This large-scale pre-training process allows it to capture a wide range of time series patterns, enabling strong performance in zero-shot generalisation. Recent concurrent work, Chronos (Ansari et al., 2024), offers a similarly broad framework for pretrained time series forecasting but adapts transformer-based language model architectures T5 (Raffel et al., 2023) to treat real-valued time series as discrete tokens. Using scaling and uniform binning, Chronos converts continuous sequences into a fixed vocabulary. Once tokenised, it trains a language model on an extensive collection of public and synthetic time series datasets, thus learning to model a wide range of temporal patterns. Chronos demonstrates superior performance across 42 benchmark datasets, outperforming in-domain and zero-shot scenarios.

6.3 Data and Methods

6.3.1 Datasets

This section details the dataset employed to evaluate the predictive performance of deep learning and foundation models, with real-world traffic data collected via a Split Cycle Offset Optimisation Technique (SCOOT) based Urban Traffic Control system (Y. Li et al., 2025). The SCOOT uses a network of sensors to capture traffic flow data across the road network. The dataset includes traffic flows from the Glasgow City Council area over four consecutive years, from October 1, 2019, to September 30, 2023, which includes the COVID-19 pandemic period (Y. Li et al., 2024). There are 470 sensors in the SCOOT dataset which record traffic flows at 60-minute intervals.

Figure 6-1 and Figure 6-2 compare the attributes of the SCOOT dataset with other traffic flow datasets applied in recent traffic flow prediction research from 2022 to 2024 (Alvi et al., 2024; J. Chen et al., 2023; Z. Chen et al., 2022; H. Gao et al., 2022; R. He et al., 2023; X. Huang, Tang, et al., 2022; Kashyap et al., 2022; C. Ma et al., 2022b; Naheliya et al., 2024; Tan et al., 2024; X. Xu et al., 2022, 2023; Y. Zhao et al., 2024; S. Zhou et al., 2023). Most datasets cover no more than one year during normal periods and use time intervals of less than 30 minutes (Duan et al., 2022; Huo et al., 2023; Q. Jia et al., 2024; Q. Lai et al., 2023, 2023; W. Lu et al., 2024; Narmadha & Vijayakumar, 2023; Z. Wang et al., 2023; K. Wu et al., 2023; Z. Xia et al., 2024; Xing et al., 2023; B. Yan et al., 2022; D. Yang & Lv, 2023), while the SCOOT dataset covers longer than many previous studies. Although one study utilised a seven-year traffic dataset, which is longer than the SCOOT dataset, it only covers a period of stable traffic conditions. In contrast, the SCOOT dataset captures traffic flows before, during, and after COVID-19, providing valuable insights into the drastic changes in human mobility patterns in response to government mobility interventions during a period of significant disruption. Its long-term coverage allows models to capture long-term traffic trends, seasonal fluctuations, and emergency-related variations, contributing to more robust predictive performance. Besides, the bubble size in Figure 6-1 represents the number of data points, and the SCOOT dataset contains a relatively large volume of observations. This large volume of data enhances deep learning and foundation models by improving their ability to learn complex traffic patterns and reducing the risk of overfitting.

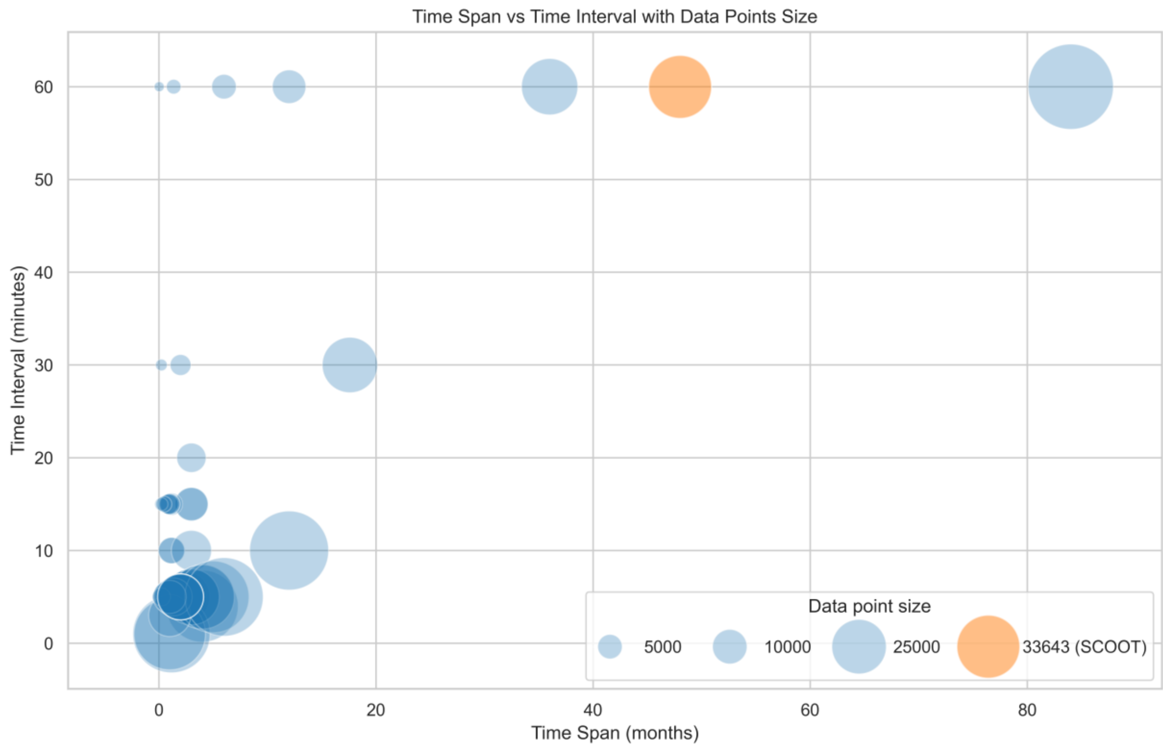

Figure 6-1. Comparison of traffic flow datasets by time span, time interval, and data volume.

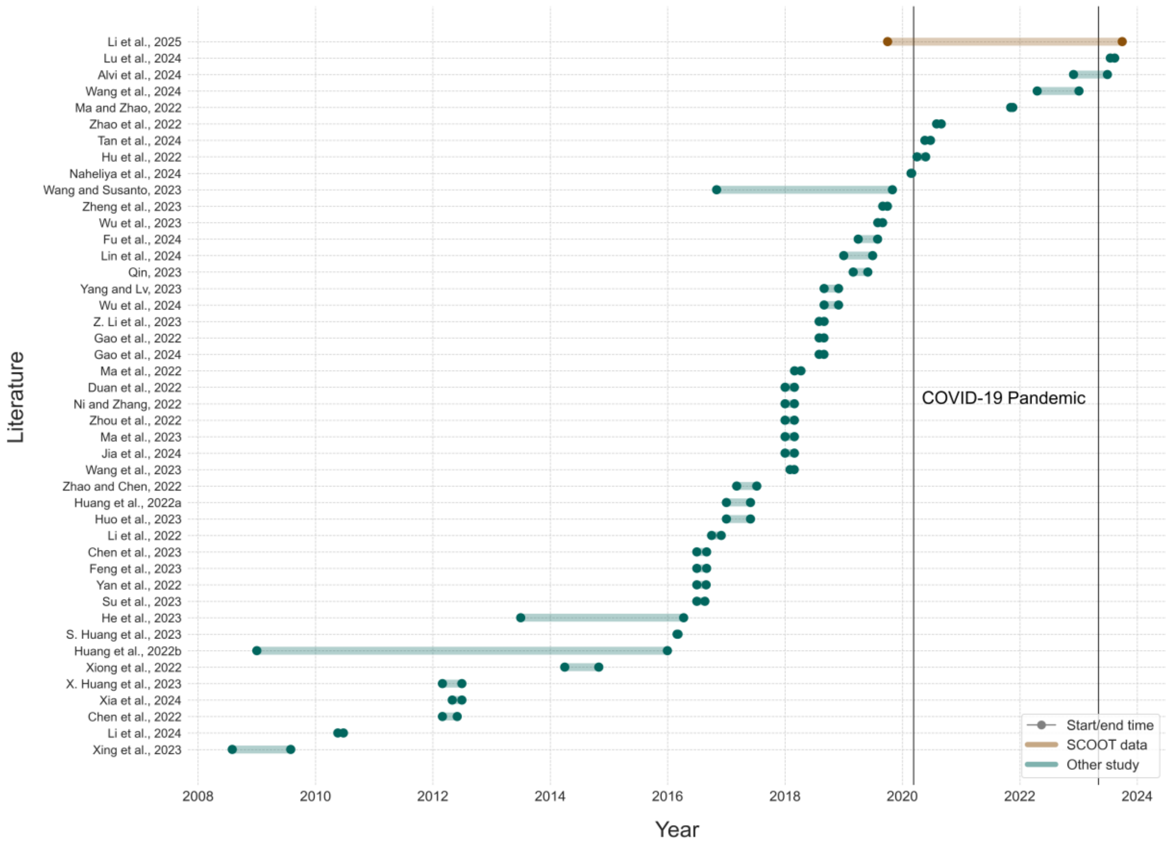

Figure 6-2. Time scope of traffic flow datasets.

6.3.2 Deep Learning and Foundation Models

We select two widely used deep learning models for time series analysis, CNN (Waibel et al., 1989), LSTM (Hochreiter & Schmidhuber, 1997) and the transformer-based model Informer (Zhou et al., 2021), as well as two recently developed time series foundation models, Lag-Llama (Rasul et al., 2024) and Chronos (Ansari et al., 2024), to assess the performance of traffic flow prediction. The details of the models are outlined as follows:

6.3.2.1 Convolutional Neural Network (CNN)

CNN (Waibel et al., 1989) captures temporal patterns by applying convolutional filters to sliding windows of sequential data. This approach effectively detects local trends and short-term dependencies, enhancing prediction accuracy. In our CNN model, two one-dimensional convolutional layers are employed, with each utilising the ReLU activation function. The first layer specifies the input shape based on the sequence length and extracts initial local features from the traffic flow data. A subsequent convolutional layer further refines these features. A max-pooling layer then reduces the dimensionality of the resulting feature maps, preserving essential representations while reducing computational cost. Finally, the network is flattened and regularised using a dropout layer to prevent overfitting before a dense layer produces forecasts over 6-time steps.

6.3.2.2 Long Short-Term Memory (LSTM)

LSTM (Hochreiter & Schmidhuber, 1997) effectively models long-term dependencies and sequential relationships in time series data through gated memory cells, which retain relevant historical information while addressing vanishing gradient issues. Our LSTM model includes two hidden layers. The first LSTM layer, configured with the tanh activation function and set to return sequences, processes the input sequence to extract temporal features and passes the entire sequence to the subsequent layer. The second LSTM layer further refines these features using the tanh activation function. Each LSTM layer is followed by a dropout layer to reduce the risk of overfitting. Finally, a dense layer with six neurons is employed for multi-step prediction.

6.3.2.3 Informer

Informer (Zhou et al., 2021) is a transformer-based model specifically designed for long-sequence time series forecasting. Unlike standard transformers, which suffer from quadratic computational complexity with respect to sequence length, Informer introduces a probabilistic sparse self-attention mechanism that selects the most informative query–key pairs, significantly reducing memory usage and computational cost. In addition, Informer applies distilling operations between attention layers to progressively reduce sequence length while preserving salient temporal information. Informer incorporates a generative decoder structure that produces multi-step forecasts in a single forward step rather than step-by-step, significantly improving inference speed for multi-step prediction tasks. In this study, the Informer model contains two encoder layers and one decoder layer, with a batch size of 32.

6.3.2.4 Lag-Llama

Lag-Llama (Rasul et al., 2024) is a foundation model for univariate probabilistic time series prediction, built on a decoder-only transformer architecture, LLaMA (Touvron, Lavril, et al., 2023). Lag-Llama was released on 7 February 2024, containing 2.45 million parameters. Lag-Llama tokenises input data by constructing lagged feature vectors using historical observations at predetermined lag intervals. These intervals include multiple standard frequencies such as quarterly, monthly, weekly, daily, hourly, and second-level frequencies. Each token also incorporates temporal covariates derived from date-time features such as hour-of-day, day-of-week, and month-of-year, enriching the representation and providing contextual information to the model. The input tokens, composed of lagged features and temporal covariates, are projected into a hidden representation and passed through a series of causally masked transformer decoder layers, employing RMSNorm and Rotary Positional Encoding (RoPE) at each attention layer. The final output from the transformer decoder is fed into a distribution head designed to predict parameters of a Student's t-distribution (degrees of freedom, mean, and scale) used for probabilistic forecasting. Detailed definitions of the lag structures and temporal covariates, including the specific lag intervals and feature construction process, are provided in the original Lag-Llama paper (Rasul et al., 2024).

Lag-Llama applies a robust scaling procedure using median and interquartile range (IQR) normalisation to handle numerical scale variations across different time series, significantly improving training stability and forecast accuracy. During training, Lag-Llama minimises the negative log-likelihood of the forecast distribution for future values. Lag-Llama is pre-trained on 27 datasets categorised into six domains: air quality, transportation, economics, nature, energy, and cloud operations. The pre-training corpus includes 7,965 univariate series consisting of about 352 million data tokens. This extensive and diverse corpus improves Lag-Llama's ability to generalise and deliver strong zero-shot forecasting performance.

6.3.2.5 Chronos

Chronos (Ansari et al., 2024) is a pre-trained probabilistic forecasting framework designed specifically for time series, built on transformer-based language models. The core innovation of Chronos is its approach to treating time series forecasting similarly to natural language modelling tasks. It achieves this by tokenising continuous time series data into discrete tokens using a two-step approach: scaling and quantisation. Firstly, Chronos tokenises time series data by scaling each series individually using mean scaling, which normalises the data based on the mean of absolute historical values. Then, the scaled data are quantised into discrete bins, forming tokens from a fixed-size vocabulary. This vocabulary includes numerical bins and special tokens such as PAD (for padding sequences to equal lengths) and EOS (end-of-sequence). Detailed descriptions of the tokenisation and scaling procedures, including bin construction and scaling strategies, are provided in the original Chronos paper (Ansari et al., 2024).

The Chronos modelling framework applied in this study was released on 13 March 2024. Chronos primarily employs variants of the T5 family of transformer-based language models, ranging from smaller models with approximately 8 million parameters to larger models of up to 710 million (Raffel et al., 2023). These models are trained in 5 sizes, named Tiny (8M), Mini (20M), Small (46M), Base (200M) and Large (710M), using a cross-entropy loss function, effectively framing regression as a classification task over discrete quantised bins. Chronos models provide probabilistic forecasts by autoregressively sampling from the learned categorical distributions and subsequently mapping these sampled tokens back to continuous numerical values via dequantisation and inverse scaling. To enhance training, Chronos utilises data augmentation methods: TSMixup, which creates augmented series through convex combinations of existing series, and KernelSynth, which generates synthetic series using Gaussian processes. Chronos was pre-trained on 28 datasets comprising publicly available datasets, including transport, retail, energy, finance, healthcare, and climate science, complemented by synthetic datasets. The comprehensive benchmark evaluation involved 42 datasets to assess in-domain and zero-shot forecasting performance.

6.3.3 Model Implementations

To evaluate the model performance on usual traffic patterns and unusual traffic dynamics, we divide the SCOOT dataset into two subgroups – the entire dataset including pandemic period, and the post-COVID-19 dataset. Based on the Stringency Index, the entire dataset contains hourly traffic flow data from October 1, 2019, to September 30, 2023, while the post-COVID-19 dataset includes data from June 3, 2022 (Hale et al., 2021). Each subgroup is chronologically divided into training (60%), validation (20%), and testing (20%) sets, with a 60-minute interval for both training and prediction. To assess the impact of context length on prediction accuracy, we train models with varying context lengths. Specifically, the context length is set to $24 \times n$ hours, where n ranges from 1 to 21, limited by the available computational memory. These context lengths are used to predict traffic flow over the next 6 hours, a common forecasting horizon in existing research (Duan et al., 2022; X. Huang, Lan, et al., 2022; Z. Su et al., 2023; D. Wu et al., 2024).

We conduct experiments with different hyperparameters for each context length and dataset to train deep learning models, selecting the best configuration for comparison. Informer is trained using its default model configuration. For all models, the evaluation metrics are computed at each forecast step and averaged across the six prediction steps to obtain the reported results. For deep learning models, which produce deterministic point predictions, the evaluation metrics are further averaged over 10 independent inference runs to reduce the randomness of individual training runs. For foundation models, Lag-Llama generates 100 samples from its predictive distribution for each forecast step, while Chronos produces predicted quantile values at 10 fixed probability levels (0.1, 0.2, ..., 0.9). The evaluation metrics for foundation models are therefore computed from aggregated predictions. The Adam optimizer is employed for training all deep learning models, with CNN and LSTM trained for 100 epochs and Informer trained for 20 epochs. The best hyperparameter settings for CNN and LSTM are summarised in Table A1 and Table A2, respectively, while he variance of evaluation metrics for each model is recorded in Table A3. Mean Square Error (MSE) is used as the loss function during the model training (Z. Wang & Bovik, 2009):

$$Loss = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \quad (6\text{-}1)$$

All the models are implemented in Python 3.12.4, and executed on a 64-bit Ubuntu server with Intel Xeon Gold 6334 8-Core Processor $\times 2$ @ 3.60GHz CPU, 125 GB of RAM, and an NVIDIA A100 GPU with 24 GB of memory. The deep learning models are developed using TensorFlow 2.17.0, while Informer and the foundation models are implemented with PyTorch 2.3.1.

6.3.4 Evaluation Metrics

The accuracy of traffic prediction models is typically evaluated using performance metrics that quantify their ability to forecast traffic conditions. In this research, we employ three widely recognised metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). RMSE and MAE assess absolute errors, while MAPE evaluates relative errors (De Gooijer & Hyndman, 2006). In all metrics, lower values indicate better prediction performance. The formulas are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{6-2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{6-3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100 \tag{6-4}$$

where y_i and $\hat{y}_i$ represent the ground truth and the predicted value for the nth traffic flow sample. n is the total number of the prediction samples.

6.4 Results

6.4.1 Model Performance Comparison

This study compares traffic flow prediction model performance across the entire dataset and post-COVID-19 dataset at different context lengths (input lengths) between deep learning and foundation models (Figure 6-3). The evaluation results clearly distinguish between model performance when trained on the post-COVID-19 dataset and the entire dataset. Across all models, evaluation metrics (MAE, MAPE and RMSE) are consistently lower for the post-COVID-19 dataset. This suggests that deep learning and foundation models perform better with stable traffic patterns. Specifically, the improvements of deep learning models are moderate, with a slight decrease in RMSE and MAPE when predicted on the post-COVID-19 dataset, suggesting that traditional deep learning models may be less sensitive to different data patterns. In contrast, foundation models demonstrate a noticeable performance gap between different datasets. When predicted on post-COVID-19 data, the reduction in MAE, MAPE and RMSE is more evident than deep learning models, particularly for Lag-LLaMA, indicating improved model adaptability to stable traffic dynamics.

According to the context length, increasing the context length leads to improved prediction performance for the foundation models, while only limited improvements are observed for the deep learning models. CNN, LSTM and Informer generally show poor performance as the context length increases. Although LSTM maintains a relatively stable trend, CNN and Informer exhibit greater performance fluctuations. In particular, CNN shows pronounced variability for longer context lengths, suggesting potential overfitting or inefficiencies in capturing long-term dependencies. Foundation models consistently reduce MAE, MAPE and RMSE as context length increases, although with slight fluctuations. Lag-LlaMA, in particular, demonstrates the most considerable improvement, reinforcing its ability to apply long historical sequences effectively. These findings highlight the superior capacity of foundation models to process and utilise long-term dependencies in time series prediction.

Although foundation models generally benefit from longer context lengths, their performance declines when the context is short—often falling behind deep learning models. In particular, Lag-LLaMA consistently yields higher MAE and RMSE values than deep learning models across all context lengths when evaluated on the full dataset. This can be attributed to the zero-shot nature of these pre-trained models, which rely on broadly learned universal patterns from large-scale, high-quality data rather than task-specific training (Ren et al., 2024). The entire dataset, which includes the more heterogeneous and unusual traffic patterns, would make the zero-shot prediction more demanding on these models. In contrast, the post-COVID-19 dataset exhibits more stable and universal traffic flow dynamics, enabling the foundation models to utilise their extensive pre-training more effectively and outperform the traditional deep learning models. Besides, the consistent performance improvements observed with longer context lengths demonstrate the importance of providing foundation models with sufficient historical information to enhance their zero-shot predictions in time series prediction.

Figure 6-3. Comparison of the post-COVID-19 and entire dataset performance (MAE, RMSE, MAPE) of models across different input lengths.

6.4.2 Training Time and Inference Time Analysis

Figure 6-4 illustrates the trade-off between training time and Mean Absolute Error (MAE) for deep learning models on the post-COVID-19 and entire datasets. For the post-COVID-19 dataset, CNN demonstrates the fastest training time at less than 1 second per epoch while achieving the best prediction performance. LSTM requires a moderately longer training time of around 6 seconds per epoch but delivers poorer performance than CNN. Notably, Informer exhibits the longest training time, yet paradoxically achieves the poorest prediction performance. This indicates that with relatively stable traffic patterns, increased model complexity and training time do not necessarily lead to improved accuracy, with the most computationally intensive model showing the weakest performance. In contrast, the entire dataset exhibits a different pattern. Although the training time trend remains consistent across models, both LSTM and Informer show modest performance improvements compared with CNN, with all the models achieving MAE values of around 28. This suggests that when dealing with more complex and irregular traffic patterns, the sophisticated temporal modelling capabilities of LSTM and Informer provide limited but observable benefits, though these improvements come at the cost of substantially increased computational demands.

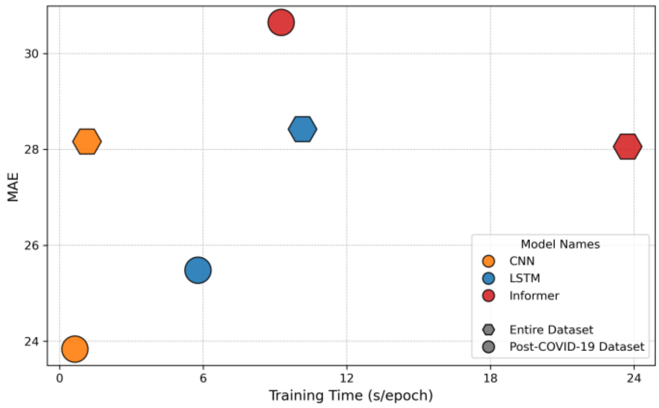

Figure 6-4. Average training time and MAE of CNN, LSTM and Informer across all context lengths (measured on NVIDIA A100 GPU).

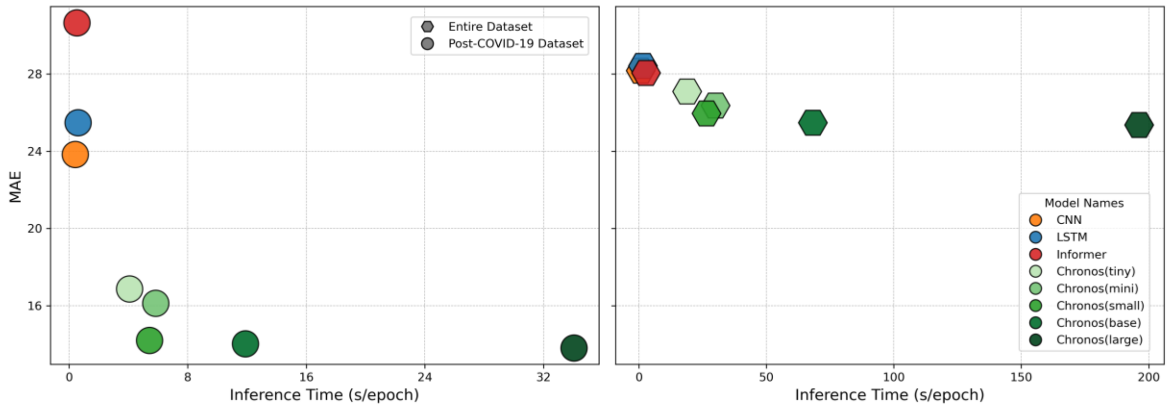

Figure 6-5. Average inference time and MAE of models across all context lengths (measured on NVIDIA A100 GPU).

We also compare the inference time for all the models, including deep learning and foundation models (Figure 6-5). It is important to note that Lag-Llama is intentionally omitted from this figure due to its exceptionally high inference times (C. Liu, Yang, et al., 2024). It requires approximately 132 seconds per epoch on the post-COVID-19 dataset and 875 seconds per epoch on the entire dataset, substantially longer than the inference times observed for the other models. For both post-COVID-19 and entire datasets, deep learning models exhibit relatively short inference times but moderately higher MAEs, while the Chronos models show a broader range of inference times that generally increase with model size. Different from the training time comparison, where Informer required significantly longer durations than CNN and LSTM, all three deep learning models show similar inference durations. This is because they all produce predictions through a single forward procedure during inference. While Informer's training is computationally intensive due to its complex self-attention mechanisms, its generative-style decoder enables efficient multi-step forecasts comparable to CNN and LSTM.

For Chronos models, larger configurations tend to achieve lower MAEs at the cost of progressively longer inference durations. This trade-off stems from Chronos's autoregressive forecasting method, where future values are generated sequentially by sampling from learned probabilistic distributions (Ansari et al., 2024). This sequential generation process, combined with increased parameter counts in larger models, leads to substantially extended inference times. A key observation is that Chronos (Small) achieves shorter inference times and better performance than Chronos (Mini), indicating that this configuration effectively balances computational efficiency and predictive accuracy. However, beyond Chronos (Small), increasing model size produces only marginal performance improvements while substantially increasing inference times, suggesting diminishing returns for larger Chronos variants in traffic flow prediction tasks.

6.4.3 Model Size Analysis

Figure 6-6 compares the average performance of different context lengths with model size, which is measured by the number of parameters. Specifically, the number of parameters for deep learning models depends on their architecture, hyperparameters, and context length, while foundation models maintain a fixed parameter number. From Figure 6-6, it is clear that deep learning models and foundation models demonstrate different performance trends as their sizes change. For foundation models, increasing the number of parameters generally leads to improved prediction accuracy on both the post-COVID-19 dataset and the entire dataset, suggesting that additional parameters help capture complex traffic patterns. In contrast, deep learning models show a negative correlation between model size and prediction accuracy on the post-COVID-19 dataset. Specifically, CNN achieves the best performance, followed by LSTM, while Informer exhibits the poorest performance despite having substantially more parameters than both CNN and LSTM. On the entire dataset, all three deep learning models converge to similar performance levels regardless of differences in model size.

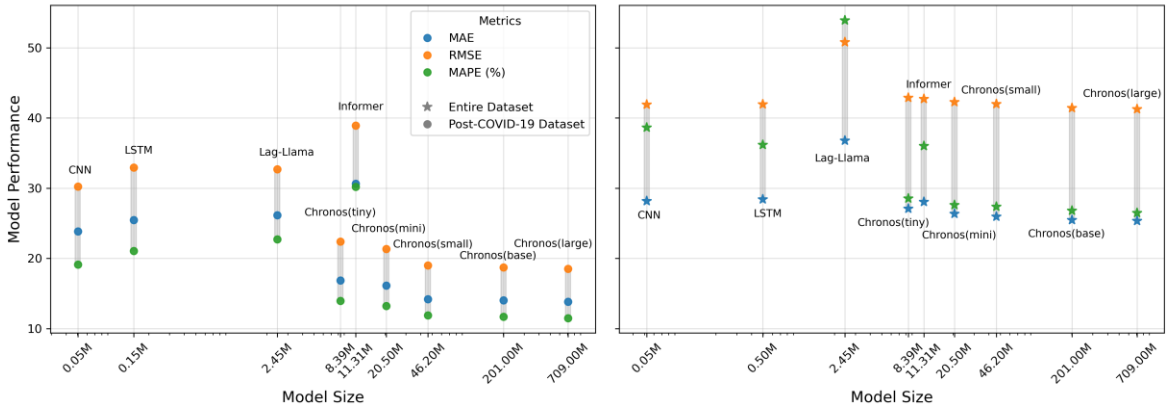

Figure 6-6. Comparison of the post-COVID-19 and entire dataset performance of models across different model sizes, averaged across all context lengths.

6.5 Discussion

In this chapter, we compare the performance of traffic flow prediction on deep learning models and cutting-edge time series foundation models. The deep learning models, CNN, LSTM and Informer, are trained on the SCOOT dataset ourselves, while Lag-Llama and Chronos are pre-trained time series foundation models, which can be applied for zero-shot prediction. We have found that foundation models with longer context lengths and larger model sizes tend to achieve higher prediction accuracy, while deep learning models show limited improvement. This suggests that deep learning models may suffer from overfitting or inefficiencies in capturing long-term dependencies. In contrast, foundation models demonstrate a superior ability to process and utilise long-term dependencies in time series prediction. However, there is a trade-off between model performance and inference time, as increasing context length and model size require more substantial computational resources. Moreover, although foundation models are more sensitive to traffic patterns, they outperform deep learning models in both usual and unusual traffic conditions, with Chronos demonstrating particularly strong performance.

In our experiments, we evaluate training and inference times separately to provide a clear understanding of the computational demands of each stage. However, for a comprehensive comparison between deep learning models and foundation models, we calculate the total running time, combining training and inference durations for the deep learning models. For foundation models, which are not trained in this study, the running time is equivalent to the inference time only. Specifically, we calculate the cumulative running time over 100 training epochs for deep learning models and one prediction epoch for all models. As shown in Figure 6-7, the running times of Chronos are significantly lower than those of other models, particularly for the small dataset. While the running time of CNN is shorter than that of Lag-Llama in this case, it overlooks hyperparameter tuning, which is essential in the deep learning training process for each prediction task. The tuning process involves testing dozens of hyperparameter combinations (Bartz et al., 2023; Yi & Bui, 2021), with each test requiring an amount of time equivalent to the running time observed here (since the inference times of deep learning models are too short to be considered). This leads to a practical running time multiple times greater than the running time here. As a result, the running time for foundation models is shorter than that of deep learning models. Besides, deep learning models require separate training for each prediction task. In contrast, pre-trained foundation models can be directly applied to different prediction tasks across various datasets with varying context lengths. This significantly simplifies model deployment and streamlines forecasting pipelines, eliminating the need for task-specific training.

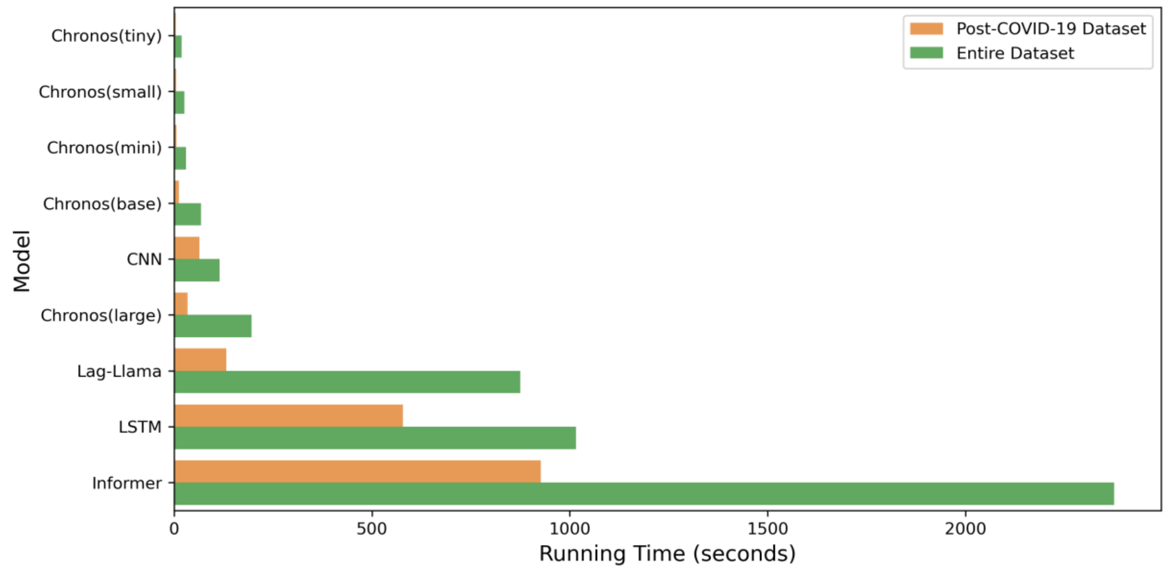

Figure 6-7. Comparison of the cumulative running time of models, averaged across all context lengths (measured on NVIDIA A100 GPU).

A key limitation of foundation models is the performance gap between different models. Our findings indicate that Lag-Llama shows only limited improvements in prediction accuracy compared to deep learning models, while Chronos consistently demonstrates strong performance across various context lengths. To further illustrate this performance gap, we used another publicly available and widely used traffic flow dataset collected by the Caltrans Performance Measurement System (PeMS) in California, USA from January 1 to December 31, 2018. As shown in Figure 6-8, the results are consistent with those from the SCOOT dataset in our research, with Chronos significantly outperforming Lag-Llama across all context lengths. Since both Chronos and Lag-Llama are pre-trained on a diverse set of publicly available datasets, the observed performance difference may stem from their training data. Comparing their datasets, we find that Chronos is trained on seven different datasets, while Lag-Llama uses only three. Besides, Chronos incorporates synthetic data generated using Gaussian processes to enhance its training process. The training data for Chronos ranges from 2009 to 2022, including the 2020–2021 pandemic period, allowing the model to capture mobility patterns under pandemic-related disruptions. Lag-Llama's training data is limited to 2009 and 2014–2016 and therefore does not capture pandemic-related mobility changes. This suggests that training foundation models on a more extensive and temporally diverse corpus of time series data improves zero-shot performance. Moreover, model size plays a crucial role in performance. Chronos offers models ranging from 8M (Tiny) to 710M (Large) parameters, which are significantly larger than Lag-Llama's 2.45M parameters and are likely contributing to its superior predictive accuracy.

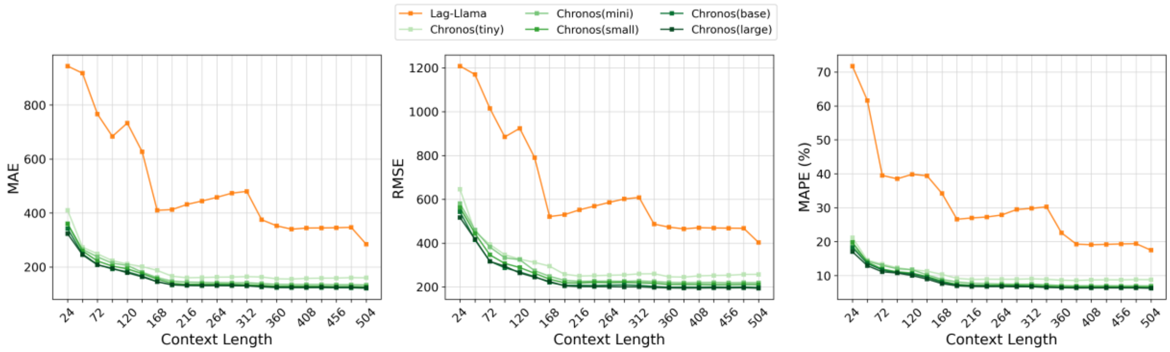

Figure 6-8. Comparison of model performance across different context lengths.

In summary, this research highlights that foundation models can achieve excellent zero-shot performance in traffic flow prediction under both normal conditions and disruptive events. Unlike deep learning models, which require extensive task-specific training and domain expertise, pre-trained foundation models can be directly applied to datasets with different data sizes, traffic dynamics, and context lengths. Besides, while deep learning models require large-scale historical data for training and validation, foundation models can make accurate zero-shot predictions with only a small subset of contextual data. Those advantages can address critical limitations of deep learning methods, such as time-consuming training processes, overfitting due to task-specific model training, and limited generalisation capabilities. Additionally, they can contribute to the practical deployment of traffic prediction models across diverse and dynamically changing urban scenarios. However, choosing an appropriate foundation model is crucial, as performance depends on factors such as training data diversity, time coverage, and model size. A well-trained foundation model with a comprehensive dataset is more likely to achieve superior zero-shot performance, making it a practical and efficient choice for real-world traffic prediction applications.

Using foundation models for traffic flow prediction and other time series analysis tasks in urban settings presents both opportunities and challenges. The development of foundation models has been one of the fastest-growing areas over the past two and a half years, since OpenAI released the first version of ChatGPT 3.5 on November 2022. As foundation models continue to evolve in both capability and efficiency, the prediction accuracy of time series foundation models is expected to improve correspondingly. Accordingly, the results presented in this study represent a baseline, reflecting the performance of the foundation models available at the time of experimentation in a zero-shot setting. Future research may extend these experiments with more recent models and with adaptation strategies such as fine-tuning or few-shot learning, and explore spatial–temporal architectures to further improve prediction accuracy and better capture the underlying dynamics of urban traffic systems. As we observed in this research, although foundation models exhibit superior performance in this research, with faster inference and higher accuracy, they still have several limitations. Firstly, the training process of foundation models is typically very expensive and time-consuming, making it less accessible for academic institutions or small research groups to extend or revise pre-trained models. Furthermore, the efficiency of foundation models heavily relies on the underlying pre-trained architectures, and the most advanced foundation models are often closed-source and developed by leading companies in generative AI. As a result, most researchers can only rely on "less advanced" or "older generation" publicly available foundation models to design fine-tuned models for time series prediction. In the future, a better collaboration between AI companies and academia is necessary to enable further customised model development. Lastly, the limited scope and diversity of training data (Ansari et al., 2024) for time-series foundation models lead to performance disparities and prediction biases across foundation models. Future work can focus on building and maintaining large-scale, diverse traffic datasets to improve model training and predictive accuracy across various scenarios. The model can also be further evaluated in regions with limited data, such as those in the Global South, to assess the effectiveness of using foundation models trained on datasets from Global North countries in different geographical contexts. Governments can encourage collaborative data-sharing initiatives between public and private sectors to expand the availability of high-quality traffic data for model development.

6.6 Chapter Summary

Making accurate traffic flow predictions using limited historical data in a short time frame is challenging. Taking Lag-Llama and Chronos as examples, we have found that both internal factors, such as model size (number of parameters) and context length of predictions, and external factors, such as the diversity and time coverage of training data, are closely related to the prediction performance of foundation models. A well-trained foundation model outperforms traditional deep learning models by providing zero-shot predictions, significantly reducing the demand on large training datasets, extensive running time, and domain-specific knowledge typically required for task-specific training. The remarkable progress of foundation models offers a valuable opportunity to simplify the deployment process and improve the accuracy of predictive models, making them more effective in diverse and dynamically changing urban traffic environments.

This chapter adds to the literature by providing a systematic empirical comparison of pre-trained foundation models and deep learning models for traffic flow prediction in a real-world, multi-year urban context that under both normal and disruptive conditions. This chapter also highlights the importance of model size and pre-training data characteristics in determining forecasting performance, providing practical guidance for transport authorities and city planners considering the integration of foundation models into intelligent traffic management systems to support adaptive and resilient urban mobility planning in both normal and disruptive conditions.

Chapter 7 Discussion and Conclusion

Urban traffic flow refers to the movement of vehicles and individuals within a city, capturing the dynamic patterns of travel. A comprehensive understanding of traffic flow is essential for managing congestion, reducing environmental impacts such as air pollution, and promoting more sustainable and efficient urban mobility systems. Currently, urban traffic flow analysis faces two common challenges: low-quality data with limited spatiotemporal resolution, and unclear traffic patterns under disruptive events and varying environment conditions. The main focus of this thesis is to improve the understanding and prediction of urban traffic flows before, during, and after COVID-19 by applying deep learning and foundation models to high-resolution traffic data and various urban indicators. Empirical studies are carried out using the data from Glasgow, UK.

Specifically, three objectives are achieved in this research. First, it introduces an openly accessible, long-term dataset that provides high spatiotemporal granularity of city-scale traffic flows in Glasgow, covering consecutive years before, during, and after the COVID-19 pandemic. Second, it develops new insights into the quantitative relationship between the spatial distribution of urban physical and social elements, including the built environment and socio-demographic characteristics, and traffic dynamics, by integrating urban big data with high-resolution traffic flow data. Third, it demonstrates how large language-based models can predict the temporal distribution of traffic flows in Glasgow under both normal conditions and disruptive events, thereby highlighting the potential of data-driven approaches to support resilient and sustainable urban mobility planning. These objectives are designed to bridge methodological and empirical gaps in the literature by integrating emerging data sources and large language-based models to better understand and forecast urban traffic behaviour across different phases of disruption.

Despite the breadth of existing research on urban traffic flow analysis, several gaps are identified across the literature reviewed in this thesis. Existing transport demand modelling frameworks demonstrate limitations in capturing dynamic, disruption-driven behavioural changes in response to the COVID-19 pandemic. Spatial and temporal determinants of traffic flows have often been analysed separately, and the combined influence of pandemic restrictions and surrounding environmental factors on traffic dynamics remains insufficiently understood. The potential of emerging urban big data sources such as street-level imagery also remains underexplored. In terms of methodology, a significant gap exists in the systematic evaluation of advanced prediction models under disruptive traffic conditions, with many models limited by overfitting and poor generalisability. Existing datasets further suffer from low spatio-temporal resolution and inconsistent quality, restricting their effectiveness in capturing accurate traffic flow patterns across long time periods. These gaps directly motivate the three empirical studies of this thesis.

This chapter summarises the major findings, highlighting the contributions of this research to the fields of urban transport analysis and prediction. As the empirical studies are an important component of this thesis, their policy implications are also discussed. Finally, the limitations of this research and potential directions for future work are presented.

7.1 Research Summary

The three research objectives of this research are addressed by Chapters 4, 5 and 6, respectively. The remainder of this section summarises the major findings, emphasising the contributions to methodology and/or substantive applications.

Chapter 4 aims to introduce a high-resolution traffic flow dataset for the Glasgow City Council area, covering four consecutive years before, during, and after the COVID-19 pandemic. Specifically, Chapter 4 attempts: (1) to address the limitations of existing traffic datasets by improving spatio-temporal granularity and coverage; (2) to generate high quality traffic flow records via data cleaning and filtering process based on spatial, temporal, and numerical filtering criteria; and (3) to validate the filtered dataset through temporal and spatial analysis, including comparisons with government stringency measures during COVID-19.

Major results of Chapter 4 include: (1) the successful construction of an intra-city traffic flow dataset with hourly temporal resolution and broad spatial coverage across all road classes in Glasgow; (2) the identification and removal of poor-quality sensor data through a rigorous multi-step filtering process; and (3) validation of the dataset's reliability by comparing traffic flow patterns with pandemic-related restrictions, revealing strong correlations between mobility levels and policy measures. These analyses confirm the dataset’s ability to reflect real-world traffic dynamics, including daily, seasonal, and pandemic-related variations.

Chapter 4 makes two key contributions. First, it provides a publicly available, long-term dataset that enhances current data resources for traffic analysis at the city scale. Second, it offers a transparent and reproducible workflow for data cleaning and aggregation, supporting future research in traffic prediction, urban mobility, and public policy analysis. This dataset serves as a critical foundation for the empirical investigations presented in chapter 5 and 6.

Chapter 5 aims to explore how urban traffic flows in Glasgow responded to the COVID-19 pandemic by integrating emerging urban big data with high-resolution traffic sensor records. Specifically, Chapter 5 focuses on: (1) evaluating the influence of the COVID-19 pandemic on urban traffic flows across four pandemic stages: ‘Before COVID-19’, ‘1st Lockdown’, ‘2nd Lockdown’, and ‘Post COVID-19’; (2) incorporating multi-source urban indicators into the analysis of traffic dynamics, including road characteristics, socio-demographics, land use patterns, POIs and GSV imagery; and (3) exploring the quantitative relationships between these urban physical and social elements and pandemic-period traffic changes using spatial econometric models.

There are several interesting findings in Chapter 5. Taking the city of Glasgow as the case study, the analysis reveals that: (1) urban traffic flows are strongly associated with socio-demographic and environmental characteristics, where areas with a higher proportion of young and white residents are associated with higher traffic flows, while areas with more natural green space are associated with lower traffic flows; (2) heavier traffic flows are observed on major roads connecting Glasgow to surrounding towns and cities, reflecting regional commuting patterns; (3) the application of GSV imagery reveals that the influence of green space on traffic is spatially heterogeneous, with the magnitudes of its effects vary by distance; (4) the spatial dependence between adjacent neighbourhoods in terms of traffic flows and urban indicators varied across the four COVID-19 stages, indicating that the strength of spatial relationships changed in response to mobility restrictions; (5) there has been a significant decrease in long-distance travel after the COVID-19 lockdown, highlighting how external disruptions can reshape mobility patterns across time and space.

Chapter 5 makes three key contributions. First, it bridges the research gap between COVID-19-related mobility patterns and the influential factors of urban traffic flows by analysing the linear and heterogeneous relationships between traffic flows and a wide range of urban physical and social factors across different stages of the pandemic. This analysis provides a nuanced understanding of how various urban elements influence traffic dynamics under changing conditions. Second, it makes use of a long-term, high-resolution traffic flow dataset covering multiple years in Glasgow, a city that has been underrepresented in previous UK-based traffic studies. By conducting a detailed comparative analysis of traffic changes across four stages (‘Before COVID-19’, ‘1st Lockdown’, ‘2nd Lockdown’, and ‘Post COVID-19’), the chapter offers insights into how travel behaviours changes in response to different levels of public health restrictions. Third, it introduces the use of GSV imagery as an emerging source of urban big data to explore the distance-sensitive heterogeneous effects of green space on traffic flows. The chapter also uncovers changing patterns of spatial dependence between traffic flows and surrounding urban characteristics throughout the pandemic timeline. These insights are able to help urban planners and policymakers in the development of data-driven strategies for transport planning, resource allocation, and community resilience in the face of future public health emergencies.

Chapter 6 aims to present a comprehensive analysis to compare the performance of deep learning and foundation models in forecasting traffic flows across different temporal and spatial contexts. Specifically, Chapter 6 focuses on: (1) evaluating the traffic flow predictive performance of deep learning models (CNN, LSTM and Informer) and emerging time series foundation models (Lag-Llama and Chronos) using long-term traffic data; (2) comparing the prediction accuracy of those models in capturing traffic flow patterns under normal and disruptive conditions; and (3) exploring the generalisability of these models across different data sizes, traffic dynamics, and context lengths.

The important finds of Chapter 6 are: (1) time series foundation models can achieve excellent zero-shot performance in traffic flow prediction under both normal conditions and disruptive events; (2) foundation models, particularly those with longer context lengths and larger model sizes, consistently outperform traditional deep learning models in traffic flow prediction, due to their superior ability to capture and utilise long-term dependencies in time series data. In contrast, deep learning models show limited improvements with increased input length, suggesting overfitting or inefficiencies in capturing long-term dependencies; (3) while larger foundation models demonstrate improved predictive performance, they also require more computational resources, highlighting a trade-off between model accuracy and inference time; (4) despite their size, foundation models demonstrate shorter overall running times than deep learning models. This is because deep learning models require task-specific training and hyperparameter tuning, while pre-trained foundation models show strong generalisability across datasets with varying sizes, context lengths, and traffic dynamics. This greatly simplifies model deployment and streamlines forecasting pipelines; (5) time series foundation models can make accurate zero-shot predictions with only a small subset of contextual data, while deep learning models require large-scale historical data for training and validation; (6) however, model choice remains critical, as foundation models’ performance depends on factors like training data diversity, temporal coverage, and model size. Well-trained foundation models with broad and representative datasets are more likely to achieve superior zero-shot performance in real-world, dynamic traffic forecasting applications.

Chapter 6 makes three key contributions. First, it bridges the research gap by systematically comparing the performance of pre-trained time series foundation models and deep learning models for traffic flow prediction. Second, it evaluates prediction accuracy on unusual traffic patterns, an area that has been sparsely explored in previous research. By applying a dataset that covers multiple years and includes a unique global pandemic period, the study enables a more comprehensive assessment of model robustness in capturing long-term trends, seasonal fluctuations, and emergency-related variations. Third, it highlights the importance of model size and the characteristics of pre-training data in determining the performance of foundation models. In particular, it shows that larger models trained on diverse and temporally comprehensive datasets are more effective for generalisable, zero-shot traffic forecasting. The work of Chapter 6 can provide practical insights for transportation authorities and city planners interested in integrating foundation models into intelligent traffic management systems, supporting adaptive and resilient urban mobility planning in both routine and crisis conditions.

7.2 Policy Implications

There are several policy implications of the empirical results, with respect to future urban transport planning, public health emergency management, the deployment of intelligent traffic forecasting systems, and academic research across related disciplines:

(1) The study indicates that heavier traffic flows are concentrated on major arterial roads connecting Glasgow to surrounding towns and cities, reflecting strong regional commuting patterns that extend well beyond the city boundary. This finding highlights that effective transport demand management cannot be achieved by individual local authorities acting in isolation. Regional transport partnerships, such as Strathclyde Partnership for Transport, should coordinate infrastructure investment, public transport delivery, and transport demand management strategies across administrative boundaries. In particular, park-and-

ride facilities, express bus corridors, and rail capacity enhancements on key commuter routes should be prioritised based on evidence of actual traffic demand patterns.

(2) This research reveals that the influence of green space on traffic flows is spatially heterogeneous, with its effect on reducing traffic varying depending on the distance between green space and the areas generating traffic demand. This finding suggests that the benefits of urban greening for traffic reduction cannot be assumed to operate uniformly across a city, and that the effectiveness of green infrastructure as a demand management tool depends critically on its spatial configuration. Urban planners and local authorities should move beyond simply increasing the total area of green space and instead consider the strategic placement of parks, green corridors, and tree-lined streets relative to residential areas and key transport roads. For example, green infrastructure positioned within walkable distance of high-density residential neighbourhoods is more likely to reduce short car trips than equivalent green space located at the urban periphery.

(3) The results show a significant and sustained decline in long-distance travel following the COVID-19 lockdown, with travel behaviour not fully reverting to pre-pandemic baselines even after all restrictions were lifted. This provides strong empirical evidence that major external disruptions can create durable and structural shifts in travel demand rather than temporary deviations. Transport authorities and national/international government bodies, including Transport Scotland and the UK Department for Transport, should treat this finding as a basis for revising long-term transport demand forecasting models and infrastructure investment assessments. In particular, projections supporting major road and public transport investment decisions should be stress-tested against scenarios of sustained behavioural change, rather than assuming a full return to pre-crisis travel patterns. This is especially important as post-pandemic hybrid working continues to reshape commuting demand in ways that traditional four-step models were not designed to capture.

(4) This study demonstrates that time series foundation models can achieve strong zero-shot predictive performance in traffic flow forecasting without requiring task-specific training on large volumes of local historical data. This finding has direct implications for how transport authorities deploy traffic forecasting infrastructure. Rather than building task-specific deep learning systems, which require sustained historical data pipelines, large computational resources for training, and ongoing retraining as conditions change, transport agencies should consider integrating pre-trained foundation models into their

intelligent transport management systems. Before operational deployment, authorities should follow the validation framework set out in Sections 6.3.3 and 6.3.4, which provides a structured basis for evaluating model performance against local traffic conditions and establishing confidence in predictive outputs. This is particularly advantageous for smaller local authorities or those managing newly instrumented road networks, where historical data availability is limited but accurate prediction is needed to support signal control and network performance monitoring.

(5) The results show that while larger foundation models deliver improved forecasting accuracy, they also require substantially greater computational resources. This creates a meaningful trade-off between predictive performance and inference time. For transport authorities operating real-time traffic management systems, where predictions must be generated within seconds to support adaptive signal control or dynamic route guidance, this trade-off has direct operational consequences. Transport authorities deploying intelligent transport systems should explicitly specify both accuracy and latency requirements when evaluating forecasting model options. They should also evaluate models under realistic operational conditions before full deployment. The benchmarking framework developed in this thesis, which evaluates models across both normal and disrupted traffic conditions, provides a practical template for conducting such evaluations.

(6) The research findings and analytical frameworks developed in this thesis can be applied in a broader planning context beyond urban traffic management. The spatial econometric framework, which integrates multi-source urban indicators including road characteristics, socio-demographics, land use, points of interest, and street-level imagery, can be adapted by researchers and practitioners working in adjacent domains such as health geography, environmental planning, and urban deprivation analysis. These are fields where the spatial relationship between the physical environment and social outcomes is similarly complex and context dependent. For researchers in transport geography and mobility, the multi-stage pandemic comparison framework developed in Chapter 5 offers a replicable approach for studying how external disruptions reshape the spatial structure of urban mobility. It has potential applications to other disruptive events such as extreme weather, major infrastructure failures, or economic crises. For researchers in time series prediction and machine learning, the comparative evaluation of foundation models and deep learning architectures conducted in Chapter 6 uses a real-world, multi-year dataset covering both normal and crisis conditions. This work addresses a significant empirical gap and provides a methodological benchmark that can be extended to other urban forecasting domains,

including energy demand, pedestrian flow, public transport ridership, and environmental monitoring.

7.3 Limitations and Future Work

7.3.1 Limitations

The limitations of this thesis mainly associated with the data availability and diversity, as well as practical and methodological application. The following context discusses those dimensions in detail.

(1) The data refinement assumes that at least one vehicle should pass each traffic sensor on a daily basis within the Glasgow area. This assumption is used to identify and exclude sensors that record entire natural days with zero traffic flow in a long term. However, this assumption may not consistently reflect actual conditions. Extraordinary circumstances such as pandemic-related lockdowns or temporary road closures could also lead to long durations of zero traffic flow that do not necessarily reflect sensor malfunction or data quality issues. Over 200 sensors are excluded from the dataset during this step, which may remove valid observations of low-traffic conditions. While this filtering aims to improve overall data reliability, it could reduce the diversity of temporal patterns and underrepresent periods or locations characterised by minimal traffic activity.

(2) The technical validation of traffic flow dataset primarily relies on descriptive analyses and comparisons within the dataset itself. For instance, the temporal distribution of traffic flows is visualised to evaluate reasonableness, and the hourly zero frequency is compared with hourly traffic flows to validate reliability. While some statistical methods are applied, the validation process remains largely self-referential and does not incorporate external benchmarks or independent validation sources. Although the dataset is compared with the COVID-19 stringency index to demonstrate a relationship between policy measures and traffic behaviour, most validations are based on expected trends during the pandemic rather than objective ground truth.

(3) The analysis of the relationship between urban indicators and traffic flows across the COVID-19 pandemic does not differentiate between types of motor vehicles. The traffic flow data mixes all motorised vehicle types, including private cars, taxis, buses, and vans, without distinction between private and public transport. This lack of discrimination limits the ability to capture mode-specific traffic flows and behaviour patterns. For example,

public transport usage may have declined more sharply than private cars use during lockdowns, while vans may have increased in response to rising demand for home deliveries. As a result, the findings provide only a general view of traffic dynamics, rather than a comprehensive understanding of how different types of vehicles were influenced by COVID-19 restrictions and policy interventions.

(4) The traffic flow analysis does not include temporal information on changes to the physical street environment during the COVID-19 pandemic. Modifications such as the introduction of temporary pedestrian zones, expanded cycling lanes, street closures, or reduced speed limits were widely implemented in many cities to support active travel and physical distancing. These street-level interventions may have great influence on individual travel behaviour and mode choices, leading to changes in traffic flow. However, due to the lack of detailed spatial and temporal data on such interventions within the sensor coverage, their potential impact could not be incorporated into the current analysis. Therefore, the analysis may overlook contextual factors that influenced mobility patterns, particularly during lockdown and recovery periods when urban streetscapes were being actively reconfigured to support public health objectives.

(5) Although time series foundation models such as Chronos and Lag-LLaMA can outperform deep learning models in zero-shot forecasting and in adapting to disruptive traffic conditions, their broader application remains constrained by high computational demands. While the cumulative inference time of foundation models may appear shorter for specific tasks; the training process of these models is typically resource-intensive and time-consuming. This makes it difficult for academic institutions or small research groups to modify, retrain, or extend pre-trained models based on local or domain-specific needs. The reliance on pre-trained models provided by third parties limits flexibility, restricts methodological transparency, and creates barriers to further development. These constraints may limit the widespread application of foundation models in traffic research and urban planning practices.

(6) An advantage of time-series foundation models is their foundation in general-purpose training across a wide range of datasets. However, this strength also introduces an important limitation: the models' performance is heavily influenced by the diversity and time coverage of the data used during pre-training. In Chapter 6, the superior performance of Chronos compared to Lag-LLaMA are explained by its inclusion of a broader set of traffic-related time-series data during pre-training. This highlights how variations in

training data can result in differences in predictive accuracy. Therefore, the limited scope and diversity of training data for time-series foundation models lead to performance disparities and prediction biases across foundation models.

7.3.2 Future Work

Several directions for future research can be explored, including the consideration of specific vehicle types, the impact of electric vehicles, the use of other emerging mobility data, and the integration of traffic flow with road safety data.

(1) Traffic flow analysis can be extended by using data that contains information on different vehicle types, such as private cars, public transport, and active travel modes including pedestrians and cyclists. This type of data allows for a more detailed analysis of mode-specific mobility patterns and how they vary across different spatial and temporal contexts. By exploring these mobility patterns with land use data, POIs, and policy measures such as low emission zones, it becomes possible to investigate how different types of transport respond to urban functionality and external interventions. For example, changes in active travel or private car usage can be analysed within and outside low emission zones, both before and after the introduction of such regulations.

(2) With the ongoing transition towards electric vehicles (EVs), future research could examine how this transformation influences traffic flow dynamics and urban mobility patterns. EV adoption is likely to affect not only emissions and air quality but also driving behaviour, charging-related travel demand, and the temporal distribution of trips. By integrating EV data with traffic flow records, it would be possible to explore whether the increasing prevalence of EVs changes traffic patterns, for example by introducing peak demand near charging stations or changing long-distance travel flows. Such analysis would provide valuable insights into how the electrification of transport interacts with broader urban mobility systems.

(3) Future research could incorporate emerging mobility data sources to complement traditional fixed detector records and construct more comprehensive traffic flow datasets. Connected vehicle data collected from on-board sensors and vehicle-to-infrastructure communication provides high-frequency information on speed, acceleration, and location, enabling a more detailed understanding of driving behaviour and traffic dynamics in real time (Zheng & Liu, 2017; Zhou & Bridgelall, 2020). Similarly, GPS trajectories from

mobile devices, such as mobile phone-based location data (MPD), capture individual-level movement patterns across the full road network, including secondary roads where fixed detectors are limited. MPD provides detailed and timely information at lower costs, offering valuable insights into travel demand, and has shown promise in enhancing traditional analytical methods for urban and transport planning (Verduzco Torres & Raturi, 2024).

(4) Future research could also incorporate road safety data (Department for Transport, 2025) with traffic flow data to explore the relationship between traffic volume and road casualties across different locations and time periods. Road safety datasets include detailed information such as vehicle type, casualty severity, casualty class, pedestrian location, and demographic information including age and sex of the casualty (Department for Transport, 2024b, 2024c). By combining these records with sensor-based traffic flow data, it becomes possible to identify where and under what conditions traffic volumes correspond to increased risk of accidents or injuries. This integration would also contribute to analysing whether certain vehicle types, such as private cars or vans, are associated with higher casualty rates. Furthermore, exploring casualty patterns in relation to the demographic information of casualties could provide insights into the distribution of risk among different population groups.

7.4 Conclusion

Urban traffic flow is an important component of sustainable and efficient urban transport systems. This research thesis includes three empirical studies focusing on introducing a long-term, high spatio-temporal resolution traffic dataset, investigating the spatial and temporal influence of traffic patterns, and evaluating the predictive performance of deep learning and large language-based models under both normal and disrupted conditions such as the COVID-19 pandemic. The findings suggest that integrating urban indicators and emerging data sources can effectively reveal the relationships between traffic patterns and built environment factors. The application of foundation models, particularly large language models, shows strong potential for improving prediction accuracy under both regular and irregular traffic conditions. Further research is recommended to distinguish transport modes, consider the impact of EVs, incorporate other source of traffic data and road safety data. Overall, the work presented in this thesis can support data-informed urban transport planning and provide decision-making insights for city authorities and policymakers.

Appendices

1.1 KNN

Figure A-1 presents the Akaike information criterion (AIC) value distribution for different buffer sizes with four spatial weight matrices based on k-NN. According to the model selection results above, we select the buffer and spatial weight matrix based on the SDM. According to Figure A-1, the trend of AIC value among different buffer sizes presents consistent variation across four COVID-19 stages. Regardless of the spatial weight matrix selection, the AIC scores reach the lowest point at the 200-meter buffer area for SDM. The line charts in Figure A-2 also indicate that the SDM with a 200-meter buffer area for independent variables performs better than the rest. Besides, the AIC value of each SDM is almost the same in the range of k-NN according to Figure A-2, from which the model applying spatial weight matrix with 4-nearest neighbours generates the relatively highest quality. Hence, we select the 200-meter buffer and the spatial weight matrix with 4-nearest neighbours in this study.

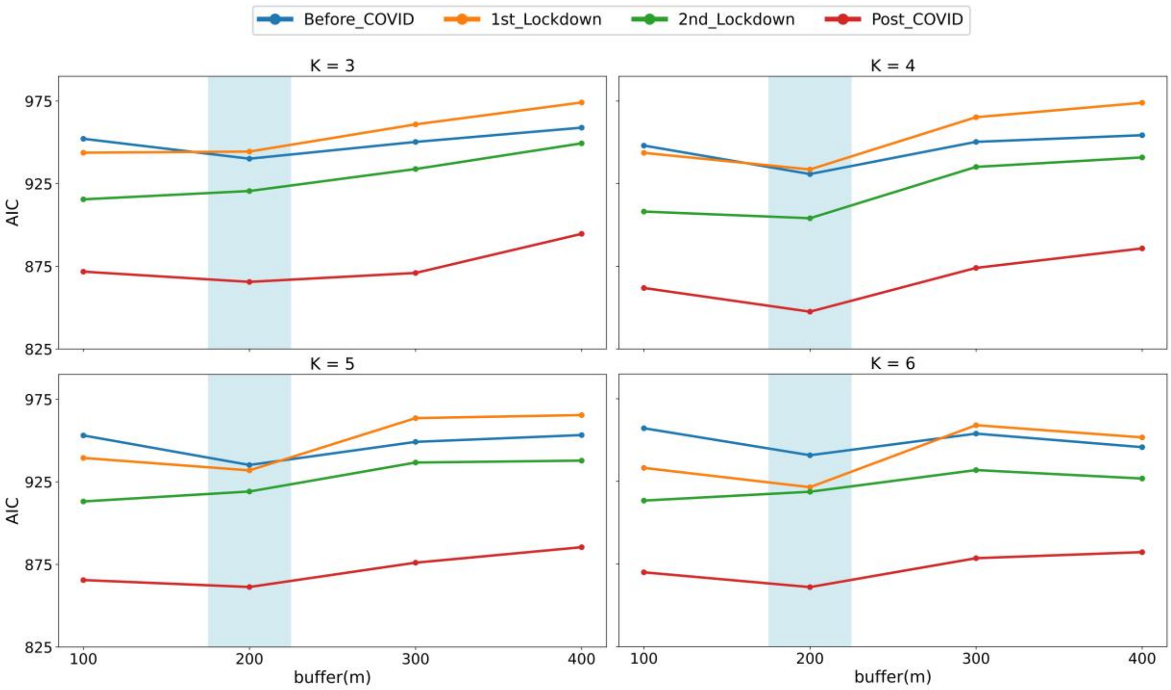

Figure A-1. The Akaike information criterion (AIC) of the spatial Durbin model (SDM) among different buffer sizes and different KNN (K = 3, 4, 5, 6) weight matrices.

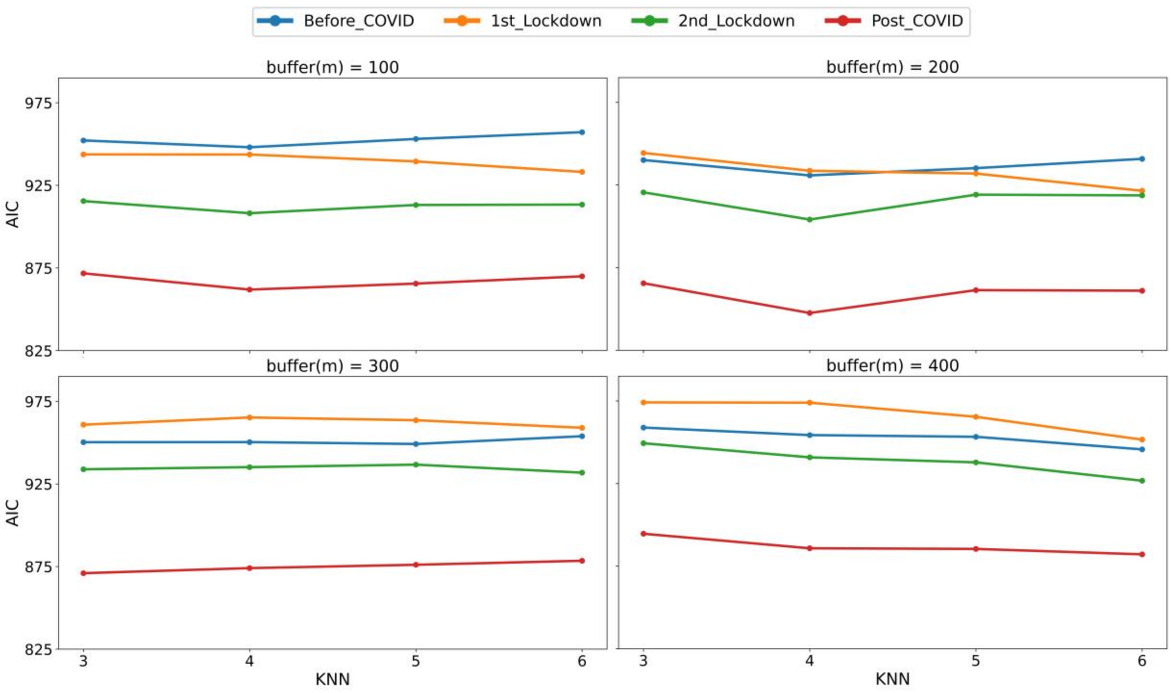

Figure A-2. The Akaike information criterion (AIC) of the spatial Durbin model (SDM) among different KNN weight matrices by the buffer size.

1.2 Street Environment

Our research uses three types of street environment-related data: land use data, POI data, and GSV images. There is only one version of land use data and GSV images throughout the study period from 2019 to 2021, while the POI data updates every three months. We selected and analysed four versions of POI data during four COVID-19 stages. Specifically, we applied ANOVA (Analysis of variance) to test the difference between four versions of POI data.

ANOVA is a statistical method used to test the statistic differences between the means of three or more independent groups. In this study, we applied ANOVA to test the differences between four groups of POI data, each corresponding to a specific stage of COVID-19. There are seven categories of POI data, and we performed an individual ANOVA for each category. The formula for ANOVA is represented as follows:

$$F = \frac{MSB}{MSW} \tag{A-1}$$

Where MSB stands for the mean sum of squares of POI numbers across the four stages of COVID-19, representing the between-group variance. MSW is the mean sum of squares of

POI numbers within each COVID-19 stage, representing the within-group variance. The F statistic is used to test the hypothesis of whether there are significant differences among the group means.

Table A-1 demonstrates that all the p-values are higher than 0.05, meaning there is not significantly difference among the four COVID-19 stages. In this case, we assume there was no obvious street environment change in our study regions during the study periods.

POI Category	F Statistic	P-value
Public Infrastructure	0.577	0.629
Education and Health	0.070	0.975
Transport	0.983	0.399
Retail	0.044	0.987
Sport and Entertainment	1.249	0.290
Accommodation, Eating and Drinking	0.219	0.882
Attractions	0.086	0.967

Table A-1. ANOVA test results of POI data.

1.3 Hyperparameters for Deep Learning Models

Table A-2 and Table A-3 present the optimal hyperparameters for CNN and LSTM, respectively, which are selected based on the lowest training loss observed during the training process. These hyperparameters are fine-tuned to ensure the best model performance across different context lengths and datasets.

Context Length	Model / Hyper-parameter / Dataset	CNN: Filters Post-COVID	Filters Entire	Kernel Size Post-COVID	Kernel Size Entire	Dropout Rate Post-COVID	Dropout Rate Entire	Learning Rate Post-COVID	Learning Rate Entire	Batch Size Post-COVID	Batch Size Entire
24		128	128	3	3	0.3	0.3	0.0005	0.0001	64	64
48		64	128	3	3	0.0	0.3	0.0005	0.0001	128	128
72		64	128	5	5	0.3	0.1	0.001	0.0001	64	64
96		64	64	3	5	0.0	0.3	0.0005	0.0001	128	32
120		64	64	3	5	0.1	0.2	0.0005	0.0005	128	128
144		32	64	2	5	0.3	0.3	0.0005	0.0001	32	128
168		32	64	2	5	0.1	0.3	0.0005	0.0005	64	64
192		128	32	3	5	0.2	0.3	0.0001	0.001	32	128
216		64	64	3	5	0.2	0.3	0.0001	0.0001	32	64
240		32	32	5	3	0.0	0.3	0.0001	0.0001	32	32
264		128	64	3	3	0.3	0.3	0.0005	0.0001	32	128
288		32	128	3	2	0.3	0.3	0.0001	0.001	32	128
312		32	32	2	3	0.1	0.3	0.0005	0.0005	128	128
336		64	32	2	3	0.2	0.3	0.0001	0.0001	32	128
360		32	32	2	2	0.3	0.2	0.0001	0.0001	64	32
384		32	32	2	3	0.1	0.3	0.0001	0.0001	128	64
408		32	32	2	3	0.1	0.3	0.001	0.0001	128	64
432		32	32	3	2	0.0	0.2	0.0001	0.0001	32	64
456		32	32	3	2	0.0	0.3	0.0001	0.0001	64	128
480		64	32	2	3	0.2	0.3	0.0001	0.0001	32	128
504		32	32	2	2	0.1	0.2	0.0001	0.0001	64	64

Table A-2. Hyperparameters of CNN.

Context Length	Model / Hyper-parameter / Dataset	LSTM							
		Hidden Units		Dropout Rate		Learning Rate		Batch Size	
		Post-COVID	Entire	Post-COVID	Entire	Post-COVID	Entire	Post-COVID	Entire
24		32	64	0.2	0.2	0.001	0.001	32	32
48		128	256	0.2	0.2	0.01	0.01	64	32
72		256	256	0.0	0.1	0.001	0.001	32	128
96		64	256	0.2	0.4	0.01	0.001	32	32
120		32	128	0.2	0.1	0.001	0.001	32	64
144		128	256	0.3	0.2	0.01	0.001	32	64
168		32	256	0.0	0.3	0.0005	0.001	32	64
192		64	256	0.2	0.4	0.01	0.001	128	32
216		128	256	0.1	0.4	0.01	0.001	32	32
240		128	64	0.1	0.4	0.01	0.005	32	64
264		128	256	0.3	0.4	0.01	0.001	32	32
288		128	64	0.0	0.3	0.01	0.001	32	64
312		64	32	0.2	0.2	0.01	0.001	64	32
336		128	256	0.3	0.1	0.01	0.01	32	64
360		128	32	0.2	0.1	0.001	0.001	32	32
384		64	256	0.2	0.3	0.01	0.001	32	64
408		128	256	0.2	0.4	0.01	0.001	32	64
432		64	128	0.3	0.4	0.01	0.001	32	64
456		64	128	0.3	0.0	0.01	0.001	32	32
480		32	256	0.4	0.1	0.01	0.001	32	64
504		128	128	0.4	0.0	0.01	0.001	32	32

Table **A**-3. Hyperparameters of LSTM.

1.4 Variance Analysis of Evaluation Metrics

Table A-4 presents the variance of evaluation metrics (MAE, RMSE, and MAPE) for all models. For deep learning models (CNN, LSTM, and Informer), the variance is computed across 10 independent inference runs to assess the stability and reproducibility of model predictions. For foundation models (Chronos and Lag-Llama), which produce deterministic outputs for a given input, variance across runs is not applicable. Instead, for all models, we report the variance of evaluation metrics across the six forecast steps, which reflects how prediction performance varies with increasing prediction horizons. Lower variance indicates more consistent performance, while higher variance suggests that model accuracy degrades or fluctuates. In particular, Lag-Llama exhibits relatively high variance, indicating that its prediction accuracy decreases markedly as the forecast horizon increases, while other models show relatively low and similar variance, with more stable performance across different prediction steps.

Model	Dataset	Post-COVID			Entire		
	Metrics (Variance across 10 runs)	MAE	RMSE	MAPE	MAE	RMSE	MAPE
CNN		5.424	5.156	3.074	0.083	0.039	2.722
LSTM		4.796	6.401	3.238	0.311	0.732	4.795
Informer		9.641	11.948	8.718	0.285	0.236	8.297
	Metrics (Variance across 6 steps)	MAE	RMSE	MAPE	MAE	RMSE	MAPE
CNN		1.876	2.778	1.402	5.997	16.718	24.111
LSTM		11.191	16.746	7.581	8.020	21.333	29.672
Informer		5.950	8.721	6.945	6.225	18.310	19.957
Lag-Llama		29.133	39.589	28.083	58.478	88.254	216.793
Chronos (Tiny)		1.624	3.104	1.200	7.087	23.276	9.922
Chronos (Mini)		1.339	2.623	0.947	6.798	24.966	8.710
Chronos (Small)		1.451	2.741	1.104	6.690	24.741	8.924
Chronos (Base)		1.573	3.001	1.219	6.292	23.642	8.725
Chronos (Large)		1.445	2.727	1.204	6.148	23.358	8.047

Table A-4. Variance of evaluation metrics for each model.

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