A Comparison of Active Travel and Vehicle Diurnal Flow Profiles to Investigate the Impact of the COVID-19 Pandemic and the New Norm

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By

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Declaration

This thesis is the original work of the author except where acknowledgment has been given. The material presented has never been submitted to Newcastle University or to any other educational establishment for purposes of obtaining a higher degree.

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Abstract

The COVID-19 pandemic affected the travel behaviour and lives of people worldwide, services were closed, and people instructed to work from home. Motorised traffic fell sharply, whilst active travel, crucial to meeting Net Zero, saw unprecedented increases. This raises the question whether pre-pandemic diurnal and weekly flow patterns remain representative of those in the post-pandemic. Data clustering is applied to multi-modal diurnal flow profiles to investigate whether they have changed through the pre-pandemic to post-pandemic era.

This thesis comprises three studies, each reflecting a particular stage of the pandemic, covering vehicle and active travel flows within Tyne and Wear, England. The first study investigates cycling flows at each specific stage of the first lockdown and showed with statistical significance that locations associated with non-commuting-shaped flows witnessed the largest increases, while commuting profiles saw a decrease. As lockdown restrictions eased, flow profiles began to show signs of a return to the pre-pandemic norm.

One of the legacies of the pandemic was pop-up active travel infrastructure, which became the focus of the second study. Pedestrian and cycle lockdown flows were compared with those a year on, and showed further signs that things were returning to normal.

As time progressed, interest grew in longer-term implications in the post-pandemic era rather than the immediate response to lockdowns. Amidst growing evidence that vehicle traffic was returning to pre-pandemic levels and given its significant contribution to carbon emissions, they were included alongside cycling flows in the final analysis. A comparison of 2019 pre-pandemic with the 2022 post-pandemic flows confirmed that within the study area, vehicle flows were indeed at 2019 levels, whilst cycling volumes were 17% higher than pre-pandemic levels. Both modes have experienced shifts in the spread of flows across the day and week, which offers insight to transport planners understanding the new-normal for transport.

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List of Abbreviations

COVID-19	Coronavirus Disease 2019
CWIS	Cycling and Walking Investment Strategy
CWIS2	Second Cycling and Walking Investment Strategy
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DfT	Department for Transport
DT	Decarbonising Transport
EATF	Emergency Active Travel Fund
GPS	Global Positioning System
LTN	Low Traffic Neighbourhood
MVC	Machine Vision Camera
NCC	Newcastle City Council
NEJTC	North East Joint Transport Committee
NIS	National Infrastructure Strategy
NZS	Net Zero Strategy
OCC	Oxford City Council
OPTICS	Ordering Points to Identify the Clustering Structure
RIS3	Road Investment Strategy 3
TADU	Traffic and Accident Data Unit
TRADS	TRAffic information DatabaSe
UK	United Kingdom of Great Britain and Northern Ireland
UTSG	University Transport Study Group
WFH	Working From Home
WHO	World Health Organization
WSS	Within Sum of Squares

Publications and Conferences

Publications

1. Burke, M., Dissanayake, D. and Bell, M., 2022. Cluster analysis of daily cycling flow profiles during COVID-19 lockdown in the UK. *Journal of Advanced Transportation*, 2022.

2. Burke, M.E., Bell, M. and Dissanayake, D., 2024. 9 to 5 or a new-normal? Cluster analysis of pre and post pandemic vehicle and cycle diurnal flow profiles. *IET Intelligent Transport Systems*.

Conferences

1. “9 to 5 or a New-Normal? Cluster Analysis of Pre and Post Pandemic Vehicle and Cycle Diurnal Flow Profiles”. Smeed Prize Entry. Presented at the 55th Annual Conference of the University Transport Study Group. Held by Cardiff University, U.K. (2023).

2. “Multi-Modal Flow Profile Analysis of a Low Traffic Neighbourhood Scheme” Presented at the 54th Annual Conference of the University Transport Study Group. Held by Edinburgh Napier University, U.K. (2022). *Also presented on my behalf as a poster by Dr Dilum Dissanayake at the TRBAM 2023 in Washington, D.C., USA*.

3. “Use of Detector Data to Analyse Cycling Trends during COVID-19”. Presented at the ITS UK Smart Environment Forum. Held at Newcastle University, U.K. (2021).

4. “Identifying Suppressed Demand to Cycle in an Urban Environment: Analysis of daily flow profiles before and during the COVID-19 pandemic using data clustering” Presented at the 53rd Annual Conference of the University Transport Study Group. Held virtually by Loughborough University, U.K. (2021).

5. “Cycling volumes during the COVID-19 Pandemic and how it can inform future investment in cycling infrastructure; A Case Study in North East England”. Presented at the WCTRS International E-Conference on Pandemics and Transport Policy. Held virtually by Hiroshima University, Japan. (2020).

Chapter 1. Introduction

1.1 Background

COVID-19 and the associated lockdowns across the globe brought about many challenges, but also some opportunities, to the transport sector. The demand to travel fell substantially during enforced lockdowns, when many worked from home (WFH) and children were taught by parents. Vehicle traffic reduced dramatically as did public transport due to social distancing guidance and passenger's fear of infection. Flights remained grounded indefinitely. Against this trend, active travel, including cycling, increased as people enjoyed streets free of traffic.

As most societies across the world are now in the 'post-pandemic era', it is time to identify whether there has been a lasting effect on the way people travel. Whilst the pandemic is something of the past, climate change remains an issue of increasing concern. Consistent with Government policy transport planners encourage cycling, not only because it offers carbon-free transport solutions but also because of the many other benefits including health improvements, better local air quality and reduced congestion. Despite these benefits being widely recognised prior to the pandemic, the lack of political will and funding were barriers to investment in cycle and walking infrastructure in England (Aldred et al., 2019), however, the increased active travel levels witnessed during the pandemic offered an opportunity to align recovery policies with the transition to Net Zero (Marsden & Docherty, 2021).

The cause of congestion and air quality exceedances in urban areas is primarily due to private motorised vehicles, the most common travel mode of people, products and services. Therefore, it is important to understand the diurnal patterns in which these vehicles flow for purposes such as transportation planning, traffic management, air quality predictions and the assessment of the impact of new developments on surrounding road network. Prior to the COVID-19 pandemic, long-standing assumptions are made regarding typical diurnal flow profiles, with emphasis on the morning and evening commute times occurring systematically every weekday. The COVID-19 pandemic has led to a need to understand whether there has been a fundamental change to both the volume and the time-of-day people chose to travel. Emerging evidence internationally suggests there may have been a shift in the way people commute by private car, with pre-pandemic patterns have been partially rejected and new ones adopted, however there is still uncertainty over long-term post-pandemic trends (Ecke et al., 2022), with new patterns being attributed to the rise of WFH arrangements (Gao & Levinson, 2022; Loo & Huang, 2022).

1.2 Motivation for Study

Many uncertainties remain within transport in the aftermath of the Pandemic, meaning some of the most fundamental assumptions regarding travel patterns need to be questioned. In the UK, many transport assessments are carried out on the assumption of "*normal traffic conditions and usage*" (Department for Levelling Up Housing and Communities, 2014) This raises the question, what can we now consider as normal traffic conditions? There is a need to know to what extent the drop in motorised traffic during the pandemic has remained in the post-pandemic era.

It is not just the assumptions regarding total daily flow volumes that need to be considered but also how these have changed across the day. These changes caused by the pandemic have been complex and therefore has created many more factors that extend beyond total daily flow volume that need to be considered when assessing the impact on travel demand. Questions that arise include: *Has there been a widespread adoption of WFH and flexible working?* and *has the distribution of travel across the day and working week in the post-pandemic era fundamentally changed?* Understanding these temporal changes is valuable for transport planning and air quality modelling going forward in the post-pandemic period.

In the case of cycling and active travel, determining whether the unprecedented increase during the pandemic has led to a long-term modal shift is important for assessing cycling targets set out in the Second Cycling and Walking Infrastructure Strategy (CWIS2) and contributing to the wider net zero targets. Moreover, changes in temporal and geospatial factors affecting cycling volumes during and after the pandemic can help inform the characteristics of trips made by bicycle. Considering both factors together indicate whether there is a prevalence of recreational or commuting activities, which can inform where and what type of cycling infrastructure in which to invest.

Early research into the lockdowns brought about by COVID-19 often used online surveys (Fatmi, 2020; Bick et al., 2021; Jain et al., 2022), a limitation of which was that they often resulted in respondent samples that were not representative of the wider populations (Akyelken & Hopkins, 2023). Moreover, without studying the post-pandemic trends, there is a limit to the insights that can be provided by these initial studies.

What did emerge, however, is a suggestion that there has been a fundamental shift in travel choices. In the pandemic, the demand for travel dropped with increased WFH, whilst flexible working altered the times of day people commuted. The mode choice of transport changed, with a decrease in motorised traffic and increase in active travel. Implications of these changes will affect the assessment and planning of transport systems to best achieve Net Zero goals into the future.

Considering the difficulties in obtaining a representative sample through online surveys, alternative sources of data were explored to investigate the impact of the pandemic on transport using an alternative approach. Moreover, it was considered imperative for a continuation of study beyond the initial lockdown period, stretching sufficiently into the post-pandemic era to obtain a realistic assessment of the 'new-normal'.

Data sources were identified that provided multi-modal time series data from a combination of inductive loop detectors and machine vision cameras. Previous time series research typically uses techniques such as Autoregressive Integrated Moving Average models (ARIMA). Whilst prior to the pandemic these models often accurately forecast future observations, problems arise with the presence of structural breaks (or level changes), large amounts of anomalies or outliers and significant changes in seasonal and trend patterns. Due to the unprecedented changes in travel behaviour outlined in this section, the COVID-19 pandemic has created all three of these issues, therefore another method was explored.

Cluster analysis of time series is a less common method to investigate traffic flow data. Whilst perhaps it is not as powerful as the likes of ARIMA for forecasting future flows, it has the potential to be more appropriate for exploratory analysis as it can be used to understand underlying patterns in data without making strong assumptions or relying on a wealth of homogenous, historical data prior to the analysis. Moreover, by focusing on the shape of diurnal flow profiles when clustering, analysis can identify the changes to daily travel patterns brought about by the pandemic described earlier, such as telecommuting and flexible working hours.

The growing availability of big data to transport planners over the past decade (Soriguera, 2012; Romanillos et al., 2016) presented the opportunity for this study. Often used only for real-time services and short-term traffic forecasting, there is an opportunity to extract the underlying patterns within the vast amounts of raw data, thus allowing it to become a useful tool for longer-term planning (Soriguera, 2012). One such method is the cluster analysis of diurnal flow profiles from historical data sets. Primarily used on motorised traffic flows (Weijermars & Van Berkum, 2005; Guardiola et al., 2014; Necula, 2015), but with the increasing awareness of the importance of sustainability, cluster analysis has been used on active travel (Li & Xu, 2021; Hernández-Vega et al., 2021) and public transport flows (Vidal et al., 2022).

Whilst there is an increasing interest in clustering the diurnal flow profiles of sustainable modes of transport, no literature was found that directly compare them with vehicle traffic, or any other mode, within the same study. The COVID-19 pandemic has presented an opportunity for a novel approach through clustering multi-modal diurnal flow profiles to investigate how each mode has been affected by each stage of the pandemic.

Identifying patterns in this data will provide insights into travel behaviour, before, during and after the pandemic crucial to the design of future infrastructure and therefore supports future policy making (Romanillos et al., 2016).

1.3 Research Questions

Given the need for a greater understanding into the impact the pandemic has had on vehicle traffic and active travel the following overarching research questions are addressed in the research reported in this thesis:

1. What impact did the COVID-19 pandemic and resultant lockdown have on cycling volumes and diurnal flow profiles? (Study 1, Chapter 5);
2. Did cycling and walking flows change in the post-pandemic period in locations where active travel infrastructure interventions occurred during the pandemic? (Study 2, Chapter 6);
3. What are the longer-term impacts of the COVID-19 pandemic on cycling volumes and diurnal flow profiles, and to what extent can the post-pandemic period be called a ‘new-normal’? (Study 3, Chapter 7);

4. How have the change in vehicle flow volumes and diurnal flow profiles differed to those of cycling between the pre-pandemic and post-pandemic era? (Study 3, Chapter 7).

1.4 Research Aim

The global aim of the study is to investigate whether there has been a fundamental shift in volume of flows of cycling and motorised vehicles and their temporal patterns across the day and week due to the COVID-19 pandemic, also assessing what effect infrastructure provision encouraged active travel so as to recommend to local authorities and policy makers.

1.5 Research Objectives

The research objectives are as follows:

1. To investigate the impact of the COVID-19 lockdown on cycling volumes and diurnal flow profiles through descriptive analysis and cluster analysis;
2. To explore whether emergency COVID-19 pandemic interventions encouraged active travel flows;
3. To determine whether pre-pandemic assumptions regarding the diurnal flow profiles are still valid in the post-pandemic;
4. To explore the requirements to create an analysis tool based on the methods developed in this research for future studies; and
5. To make recommendations aligned with national policy to Local Authorities and decision-makers based on the findings of this study.

1.6 Key dates of the COVID-19 pandemic and lockdown restrictions in England

It is essential to know the timeline of the restrictions placed on society to curb the spread of COVID-19 to answer the research questions in Section 1.3. Below is a reminder of the key dates during the COVID-19 pandemic in England. The three-tier system enabled local restrictions based on current risk levels at a regional level rather than introducing further national lockdowns. The tiers were based on risk, with levels 1 (medium), 2 (high) and 3 (very high).

26 Mar 2020:	“Stay at home” lockdown measures legally enforced,
10 May 2020:	Return to workplace if cannot work from home,
1 Jun 2020:	Phased re-opening of schools in England,
15 Jun 2020:	Non-essential shops reopen in England,
4 Jul 2020:	Pubs, restaurants and hairdressers reopen,
14 Aug 2020:	Indoor theatres, bowling alleys and soft plays reopen,
14 Sep 2020:	Social gatherings above six banned,
22 Sep 2020:	Work from Home instructions, 10pm hospitality curfew,
14 Oct 2020:	Three-tier lockdown system begins,
5 Nov 2020:	Second national lockdown legally enforced,
2 Dec 2020:	Return to three-tier lockdown system,
6 Jan 2021:	Third national lockdown legally enforced,
8 Mar 2021:	Primary and Secondary Schools open
29 Mar 2021:	“Stay at home” order lifted,
12 April 2021:	Non-essential shops and public buildings reopen
17 May 2021:	Indoor hospitality reopens
19 July 2021:	Most restrictions lifted

**Source* – (Institute for Government (2021)

1.7 Thesis Outline

Following this introduction chapter, Chapter 2 covers the literature review exploring the impact the COVID-19 pandemic has had on transport. The chapter begins with the relevant UK Government policy, focusing on the uncertainties in transport brought about by the pandemic. Longstanding transport issues that originate prior to the pandemic is explored in the next section and finally a review of the emerging research into the impact of the pandemic and the response to it is covered, identifying the gap in knowledge.

Chapter 3 provides a review of the methods employed in this study, namely cluster analysis of traffic flows in a time series format. There are many alternative approaches for this technique and each step will be described in turn. The data collection and preparation methods are discussed in the first section of the chapter whilst the second half of the chapter reviews the clustering methods themselves.

Chapter 4 begins with an overview of the methodological framework of the thesis. Beginning with a description of the case study area and its suitability as a choice to investigate the impact of the pandemic. The steps taken to identify appropriate data sources and acquire them is discussed before the data preparation steps are listed. The final section of Chapter 4 outlines the specific data analysis steps that will answer the research questions in Section 1.3 of this chapter.

Three analytical studies were carried out in this research. Chapter 5 covers Study 1, which was conducted immediately after the first lockdown in England, with a focus on the unprecedented increase in cycling during this time. How Study 1 differs from the two that follow is in the detailed analysis of cycle flows broken down into the periods of the first lockdown and restrictions imposed by the government. There was a slow easing of lockdown and this is reflected in the findings of the chapter.

Study 2 is covered in Chapter 6, developing the methodology from Study 1, introducing pedestrian flows alongside cycling. Emerging policy from the first lockdown was the creation of the Emergency Active Travel Fund (EATF), and of particular interest in terms of their influence on flow levels, therefore they were the topic of Study 2. Study 2 uses data obtained from a source different from the other two studies, namely Machine Vision Cameras that enables the capture of the pedestrian and cycling flows together.

Chapter 7 presents the last of the three studies. As time through the pandemic progressed, it became apparent that there is a need to understand the impacts of the pandemic on long-term transport patterns, and not just the situation during the lockdown of society. This required the analysis of a dataset that covered both the pre-pandemic era and post-pandemic era, something that the previous two studies were unable to do. As well as covering a more comprehensive time period, revisiting the analysis offered the opportunity to include vehicle traffic flows alongside cycling flows, being the major source of negative externalities within urban transport and to act as a comparison to the changes in cycling trends, this was considered important.

Finally, Chapter 8 will bring together the results from all three studies and discusses the findings in the context of the previous literature that dealt with travel during the pandemic, before providing recommendations to transport planners and decision makers with due consideration of the current policy. The suitability of the methodology is discussed along with the limitations of this research. Conclusions are drawn and recommendations for further research on this topic that will influence transport for the foreseeable future draws the thesis to a close.

The following chapter consists of the literature review that will inform this research, covering UK transport policy, long-standing issues faced within the transport sector and how these are being affected by the COVID-19 pandemic.

Chapter 2. Literature Review

2.1 Introduction

The previous chapter outlined key research questions within the transport sector that have emerged in the wake of the COVID-19 pandemic. Investigating these questions will help address some of the most pressing transport issues as we move beyond the pandemic, particularly in relation to the goal of increasing active travel to meet Net Zero targets. This chapter reviews current transport policy and academic literature, which is essential before developing a methodology to answer these questions.

This chapter begins by identifying important topics to be researched in light of the pandemic through a review of current UK Transport Policy (Section 2.2) and Local Transport policy (Section 2.3). An introduction to the long-standing issues the transport sector faces, focusing on the impact of growing levels of vehicle traffic in urban areas prior to the pandemic is then outlined in Section 2.4. On-going obstacles to increasing cycling volumes are reviewed in Section 2.5. whilst the emerging effect of telecommuting is covered in Section 2.6. This background knowledge enables the effect of the COVID-19 pandemic on travel behaviour to be put into a wider context. Section 2.7 reviews academic research analysing the effect of the COVID-19 pandemic on travel demand (2.7.1) and how it has affected vehicle traffic (2.7.2) and cycling (2.7.3) in different ways. Transport interventions during the pandemic to encourage active travel are reviewed in Section 2.7.3. Finally, Section 2.8 summarises the findings and identify the research gap the pandemic has presented for this study.

Whilst each section in this chapter broadens the understanding of the research topic, some of the sections are more relevant to certain research questions than others. Section 2.7.1 spans all research questions as it identifies the reasons behind the general change in travel demand during the pandemic and is relevant to each research question.

However, Section 2.7.3 focuses on previous research into cycling, providing the background necessary to answer the first research question: *“What quantifiable impact did the COVID-19 pandemic and resultant lockdown have on cycling volumes and diurnal flow profiles?”* and the third research question: *“What are the longer-term* *impacts of the COVID-19 pandemic on cycling volumes and diurnal flow profiles, and to what extent can the post-pandemic period be called a 'new normal'?"*

The policy review section, particularly 2.2.6, explains that one significant policy that emerged during the pandemic was reallocating road space from vehicles to active travel through Emergency Active Travel Fund (EATF) schemes. Section 2.7.4 discusses other research into EATF schemes, informing the second research question: *"Did cycling and walking flows change in the post-pandemic period in locations where active travel infrastructure interventions occurred during the pandemic?"* Assessing whether removing vehicle traffic increased active travel use is crucial for future policy, as it could still be used to encourage a modal shift if proven beneficial. The importance of segregating cyclists from vehicle traffic is underlined in Section 2.5, which highlights the barriers to cycling, emphasising that the perception of danger when not segregated from vehicle traffic is the most significant limiting factor.

Finally, the review of national policy (Section 2.2) and local policy (Section 2.3) outlines the impact of vehicles on the transport system and wider society. Section 2.4 reviews academic literature that covers the issues with vehicle traffic in urban environments. These sections collectively inform the final research question: *"How have changes in vehicle flow volumes and diurnal flow profiles differed from those of cycling between the pre-pandemic and post-pandemic eras?"*

2.2 Review of UK Transport Policy

Government policy outlines the challenges faced within the transport sector and therefore can be used to identify important areas for research. Climate change has been and remains one of the main topics within policy over the last decade, however policy emerging since the pandemic also considers the uncertainty caused by COVID-19. This section is a top-down review of relevant policy, beginning with climate change (Net Zero Strategy), then visiting policy that outlines the role all types of infrastructure will play to support Net Zero (National Infrastructure Strategy (NIS)), followed by the transport interventions within infrastructure (Decarbonising Transport). Finally, policy documents specific to road investment, the Road Investment Strategy (RIS) and active travel, the Second Cycle and Walking Investment Strategy (CWIS2) are covered.

2.2.1 Net Zero Strategy: Build Back Greener (October 2021)

The Net Zero Strategy (NZS), (DfBEIS, 2021) sets out the course which the UK will take to satisfy the requirements of the 2008 Climate Change Act, currently with the target of achieving net zero by reducing greenhouse gas emissions by 100% by 2050. The NZS likens societies' current position to a "crossroads", as we leave the pandemic behind there is a choice to be made. Going back to the ways things used to be will not be sufficient to prevent the worst effects of climate change.

As the overarching UK Government document relating to climate change, transport comprises one of seven areas targeted for emission reductions alongside others such as power and industry. Ambitions covered in more detail within the Decarbonising Transport plan are stated. These include electrification of vehicles, both privately and publicly owned, is a major focus whilst £2bn is proposed for the promotion of active travel and £3bn for public transport improvement.

There is a clear message that the pandemic has shown policy makers what can be achieved with greater active travel levels. Electrification of vehicles will not suffice as a car-led recovery must be avoided in favour of promoting active travel and public transport use, not just for the carbon reduction but also to improve air quality, reduce noise and alleviate congestion alongside public health and wellbeing considerations.

Further encouragement to local authorities to reallocate road space to active travel is given, stating COVID-19 has allowed a rethink of the built environment and the sense of place, with measures such as segregated traffic lanes, direct cycle routes and the implementation of Low Traffic Neighbourhoods (LTN), and school streets.

However, the uncertainty surrounding the changes during the pandemic are evident in the NZS which assumes in the long term, that there will be "no long-term behavioural change due to the pandemic".

2.2.2 National Infrastructure Strategy (November 2020)

The National Infrastructure Strategy (HM Treasury, 2020) sets out how the government will support the economy through infrastructure investment whilst meeting the net zero targets. As well as transport, the strategy covers energy, flood risk management, digital communications, water, and waste. A case is made for investment in transport infrastructure. Pre-COVID, the UK had some of the highest levels of road congestion in Europe whilst the quality of its road infrastructure ranked

36th in the world according to the World Economic Forum, much lower than comparable European economies. However, the National Infrastructure Strategy states transport has been the most severely affected sector by the pandemic and therefore research is required for the government to understand what lasting effects changes in transport resulting from the pandemic will have on infrastructure and what the implications are for policy. Contradicting the NZS, it is predicted there will be long-terms implications, with more WFH likely and the surge in cycling seen over the summer of 2020 may remain.

NIS states that whilst building roads is appropriate in some instances, it will not solely solve the country's congestion problems, and that current road space needs to be used more effectively. Increasing walking and cycling can improve air quality, combat climate change whilst improving health and wellbeing, addressing inequalities and reduce road congestion. If infrastructure is experiencing less road traffic demand at peak hours and more cycling as a long-term COVID-19 effect, the case for reallocation of road space to more sustainable modes is strengthened.

2.2.3 Decarbonising Transport (July 2021)

Decarbonising Transport was published by the Department for Transport (DfT) in July 2021 (DfT, 2021a). As well as promoting sustainable modes, one of the key messages is that roads will continue to require high investment to ensure both the functioning of the UK and the reduction of congestion as a major source of carbon emissions.

However, there is a new requirement to review decisions on major transport infrastructure projects in light of the pandemic. Therefore, transport infrastructure programmes, particularly long-term, major ones, envisioned before the pandemic, need to be reviewed and scrutinised to understand whether changes in travel demand and modal shifts have remained in the post-pandemic period may mean they are no longer fit for purpose.

The pandemic has accelerated the trends in WFH, online shopping and virtual meetings that seem to be here to stay. This has resulted in fundamental changes in commuting, shopping, and business travel, which before the pandemic made up 30% of all road journeys by distance, and crucially a much higher proportion at the times and places of greatest pressure. This point is key to understanding whether our road space is being used optimally in the post-pandemic era.

Decarbonising Transport also states that the sustainable travel habits experienced during the pandemic, i.e., active travel uptake, need to be encouraged going forward.

2.2.4 Developing the third Road Investment Strategy (December 2021)

The RIS outlines the strategy for investment and management of the strategic road network in England. The second RIS was published on the 11th March 2020, immediately before the first lockdown of the UK and therefore does not take into consideration the fundamental changes experienced in transport as a result of the COVID-19 pandemic. However, the DfT published “Planning ahead for the Strategic Road Network: Developing the third RIS in December 2021 (DfT, 2021b) which considers the impact of the pandemic and its effect on the viability of future road investment. With the potential of a ‘new-norm’, understanding the future changes in travel demand is essential to ensuring investments are worthwhile. However, the RIS3 suggests that at the time of publication, overall traffic volumes have returned to pre-pandemic levels, however there may be changes to the spread of traffic across the day. Moreover, whether these patterns remain in the mid to long term future remains an unknown.

2.2.5 Cycling and Walking Investment Strategy 2 (July 2022) and Gear Change (July 2020)

The CWIS2 sets out the aims for the DfT for walking and cycling modes of transport beyond 2025 (DfT, 2022). The principles remain largely the same as the original CWIS, but the targets are made even more ambitious for pedestrian activity. Whilst the target for cycling is to double the number of trips cycled from 2018 levels by 2025, the target for average annual walking trips have been increased from 300 to 365 (once a day). Gear Change (DfT, 2020b) is the Government document containing the detail of how these targets will be achieved, covering many aspects such as core design principles (e.g. segregation of modes) and governance (e.g. the delegation of power to local authorities).

Gear change states that a fundamental issue urban roads in the UK face is the uneven allocation of road space, with motorised vehicles given the majority when pedestrian volumes can be much higher. Moreover, it states that pedestrian data is often not even available. Therefore, to address this issue Gear Change requests street audits to be conducted. However, methods to compare and contrast active travel flows across different sites are needed because if available would be of substantial benefit to assist in the design of a balanced allocation of road space.

2.2.6 Active Travel Funding

There is an urgent need to make changes now, not doing so will see people revert back to old behaviours. Like many other parts of the world, the lockdown resulted in a substantial fall in motorised traffic in the UK, to a volume that was incomprehensible at the start of 2020. On the 9th of May 2020, the UK DfT announced a £250 million EATF to accommodate the “unprecedented levels of walking and cycling during the pandemic” to incentivise people to opt for these modes over public transport, where social distancing was more difficult. The EATF was fast-tracked statutory guidance as part of the previously mentioned £2 billion investment revealed earlier in the year that encouraged regional governments, known as combined or local authorities in the UK, to reallocate road space for significantly increased numbers of cyclists and pedestrians that the UK was witnessing (DfT, 2020a).

2.3 Review of Local Policy – North East Transport Plan

The North East Transport Plan (NETP) covers the study area of Tyne and Wear alongside neighbouring counties Durham and Northumberland. The plan sets out the transport priorities for the region between 2021 - 2035, recognising the different needs of communities and how journeys can be improved. The objectives of the plan are as follows:

- Provide carbon-neutral transport;
- Overcome inequality and grow our economy;
- Create a healthier North East;
- Offer appealing sustainable transport choices; and
- Ensure a safe, secure network.

The North East has the lowest transport CO_2 emissions per capita outside London, putting it in a stronger position than other regions to achieve the net zero targets set in national policy. That being said, there is still a need for improvement in the North

East, with road transport in the region contributes 37% of the total North East carbon emissions, more than any other sector.

This can mainly be attributed to private car use. Pre-COVID, nearly 600,000 commuters travelled by private car, more than twice of all other modes combined. This results in peak time traffic congestion, emissions, poor air quality, environmental damage and land-take for roads and car parking space. With rising levels of car ownership in the region, congestion could increase if better alternatives are not offered.

However, the COVID-19 pandemic generated a dramatic fall in vehicle traffic across the North East, and at the end of March 2020, weekday traffic had reduced by 60%, resulting in less congestion and improved air quality. This was only temporary as by October 2020, road traffic volumes had recovered to just 13% below pre-pandemic levels. Importantly, whilst traffic volumes were returning by this time, there has been a change in the time of day people travel, with a reduction in the traditional peak-time traffic volumes.

This could be largely attributed to the increased prevalence of WFH. It was estimated that 27% of the region's population WFH in late 2020, and whilst it is expected that these rates will decrease it will not return to pre-COVID levels.

In contrast to road traffic, walking and cycling saw considerable increases of 37% and 15%, respectively during the height out the COVID-19 pandemic (April – July 2020). Cycling was even up by 100% in some areas. It is suggested in the NETP that this has been fuelled by a greater uptake in active travel from families, and surveys indicate they intend to keep this up once pandemic restrictions are lifted.

To ensure social distancing could be maintained with the added demand to walk and cycle, £2.2m has been spent as part of the Emergency Active Travel Fund in the region for the reallocation of road space to prioritise active travel. This was part of the wider Active Travel Fund, which provided the region with a further £9m to continue reallocating road space to pedestrians and cyclists on a permanent basis. Finally, the NETP states that in line with DfT's "Gear Change", safer and more inclusive streets are vital not just as a response to the pandemic, but for the future of the region.

2.4 Issues with Vehicle Traffic in Urban Transport

The negative externalities associated with rising private vehicle use, particularly in an urban environment, have been known for some time. As early as 1942, Sir Alker Tripp detailed safety concerns for vulnerable road users resulting from increased and faster road traffic in *Town Planning and Road Traffic* (Tripp, 1942). The proposed measures to remedy this growing urban issue are remarkably similar to the low traffic measures implemented during the pandemic. Modal filters, segregated cycle lanes, less through-traffic, and more priority for pedestrians in shopping locations were some of the solutions Tripp suggested.

Another seminal transport document of the 20th century was *Traffic in Towns*, written two decades later by Sir Colin Buchanan in 1963. The report was published against a backdrop of escalating car ownership in Britain and rebuilding of towns and cities that still bore the scars of the Second World War. *Traffic in Towns* proved to be hugely influential, yet somewhat controversial, in shaping the urban environment over the next couple of decades. The report predicted that private car ownership would not be superseded by any other form of transport in the then, *'near future'*. As a consequence, there would need to be a trade-off between ease of car accessibility and the quality of the urban environment without substantial investment in infrastructure (Buchanan, 1963).. In a review of his own report 20 years later, Buchanan admitted he had not considered the possibility of a third scenario, where neither car accessibility was restricted, nor infrastructure receiving sufficient investment – leading to a decline in the urban environment that makes sustainable transport modes even less attractive (Buchanan, 1983).

Moving forward in time, Banister (2005) outlines the key issues that need to be addressed if transport is to become truly sustainable in the 21st century. The main challenges of which, consistent with Tripp and Buchanan statements in the previous century, are centred around the growing dependence on the car in urban areas.

1. Growing congestion in urban areas has been increasing in intensity and duration;
2. Increasing air pollution has reduced the quality of urban life and resulted in health issues of the local population;

3. Traffic is a major source of noise in cities and has additional impact on people's health and the quality of the urban environment;
4. Road safety is a major concern and whilst collision rates are declining in cities with high levels of private vehicle use, they are increasing in areas with lower, growing levels of traffic;
5. Transport contributes to the degradation of urban landscapes as a result of the construction of new roads and transport facilities, the destruction of historic buildings and consequential reductions of open space;
6. The use of space by traffic also has a severance effect in neighbourhoods and other road users such as pedestrians and cyclists; and
7. Finally, at a global level, transport is currently dependent on oil and therefore is a significant contributor to CO_2 emissions worldwide.

There is evidence to suggest the negative externalities of congestion Banister (2005) states is not distributed evenly temporally across the day and week. For example, the morning commute has been extensively studied (Gao & Levinson, 2022) and often identified as the biggest problem in traffic congestion theory when the most recurrent delay caused by congestion occurs (Noland & Small, 1995). This has to be considered in Transport Planning, for example the DfT guidance states that Transport Assessments should be based on *"normal traffic flow and usage conditions (e.g. during school terms, typical weather conditions) but it may be necessary to consider the implications for any regular peak traffic and usage periods (such as rush hours)"* (Department for Levelling Up Housing and Communities, 2014). If there has been a fundamental shift in diurnal traffic patterns in the post-pandemic era this will have a significant impact on how Transport Assessments and any other Transport Planning task is dealt with in the future.

2.5 Barriers to Cycling as a form of Urban Transport

Section 2.4 has highlighted some of the key issues with motorised vehicles, particularly when used in urban areas. The review of national transport policy in Section 2.2 identified the UK Government's ambition to make cycling and walking the natural choice for many journeys over private car (DfT, 2020b). Of these two active, sustainable modes, cycling is of particular interest not just because it saw an unprecedented increase in use during lockdown, but also because it can be the fastest door-to-door option for urban journeys during peak hours when traffic congestion is at its greatest (Parkin, 2018).

However, prior to the COVID-19 pandemic, the UK was expected to fail to achieve the target set out in the CWIS to *"double cycling, where cycling activity is measured as the estimated total number of cycle stages (where a "stage" is a trip, or part of a longer trip, that also involves another form of transport) made each year, from 0.8 billion stages in 2013 to 1.6 billion stages in 2025"* (Bicycle Association, 2020; DfT, 2022). Before reviewing how the pandemic has affected cycling, it is important to understand the barriers to cycling which existed prior to the pandemic and whether they can help explain the patterns in use during and after.

A review of the literature on cycling prior to the pandemic shows the expected failure to meet the targets in the CWIS can be attributed to overarching factors. Historically, cycling has been grouped with walking as a "slow mode." There is a limited budget and level of expertise available to implement cycling schemes, leading to political barriers. These are particularly notable at a local level, where decision-makers fear that cycle infrastructure plans, which may impact motorised vehicles, will reduce the chance of re-election due to their controversy (Aldred et al., 2019).

This lack of investment in safe infrastructure, segregated from motorised vehicles, risks stifling the number of new cyclists. Individuals that are less confident or feel under-represented within the cycling community, such as women, disabled people, and ethnic minority groups need greater support and encouragement to switch to cycling (Steinbach et al., 2011; Dissanayake, 2017).

One of the main barriers to less-confident individuals to take-up cycling is the perceived danger from motorised vehicles, preferring more segregation from traffic. Rossetti et al. (2019) adopts a methodology using a stated-preference survey to analyse cycling infrastructure preferences in Santiago, Chile, finding that regular commute cyclists were less affected by lack of infrastructure and preferred more direct, on-street routes. One of the recommendations made by Rossetti et al. (2019) is to target infrastructure improvements in areas more likely to attract recreational trips, such as near parks, to benefit less-confident most.

Preferred route identification was introduced to this area of research through the use of Global Positioning System (GPS). Broach et al. (2012) used GPS trackers to monitor the route choice of 164 cyclists in Portland, Oregon, finding that generally people were willing to travel further to avoid busy, un-signalised intersections and to use segregated cycle paths. However, those who were less sensitive to infrastructure provision tended to be commuters making regular journeys. Like Broach et al., Kircher (2018) uses GPS tracking to complement a questionnaire survey in Linkoping, Sweden. Participants are divided into four competence categories, ranging from '*comfort'* to '*fast*' cyclists. Similar results are found to Broach et al., with the *fast* cyclists finding formalised cycling infrastructure such as signalled junctions slows-down their journey the most, whereas the *comfort* cyclists preferred them. The opposite could be said when encountering roundabouts; *comfort* cyclists were slowed most due to the fact that they would tend to dismount and push the bike across each arm of the junction. The *fast* cyclists, however, would navigate the roundabouts on-road and therefore typically save time over travelling through a signalised junction.

However, it is not just less-confident cyclists that value separation from traffic. Mertens and Van Dyck (2016) use a stated-preference survey to identify middle-aged (45-65) year olds in Flanders, Belgium to identify which physical factors of a street most influence its appeal for cycling. Snowball sampling was used to gather responses from 1,950 respondents, approximately 80% of which cycled weekly. Images of streets were photo-shopped to demonstrate different changes to the environment and respondents were asked to state their preference. It was identified that the best strategy to appeal to these relatively confident cyclists was to provide segregated cycle lanes. Where this was not possible, slowing and reducing vehicle traffic was the next important issue, ahead of the quality of the cycle path itself.

Research shows that demographics play a key role in the confidence of cyclists. Gender often is found in studies to influence tendency to cycle. Broach et al. (2012) found those who stated they frequently cycle in their sample were most likely to be male. Teschke et al. (2017) is a census-based study that compares the share of male and female bike commuters according to proximity to bikeways in the Canadian cities Montréal and Vancouver. Connected networks, less slopes and proximity to a bikeway all increase mode share locally. However, Teschke et al. (2017) finds that whilst women appear to be put-off from cycling more than men where overall cycling levels are low, once 7% mode share of all trips is reached, the gender split tends to be even.

Conversely, Song et al. (2017) did not find a statistically significant relationship between distance to new walking and cycling infrastructure and modal shift in a study across three U.K. case studies in Cardiff, Southampton and Kenilworth. The panel survey executed between 2010 and 2012 found higher education, white ethnicity and being male were all statistically significant. As the data was collected in the aftermath of the last major global crisis prior to the COVID-19 pandemic, the 2008 global financial crisis, Song et al. (2017) investigated shifts in employment status, finding that recent loss of employment had a positive effect on mode shift to cycling. This is attributed to the respondents not requiring to commute to a job but instead having more time on their hands to both cycle recreationally and for utility trips. Whilst the new infrastructure was used more often for recreational purposes, previous studies have shown that cyclists often start with recreational trips before they use it as a mode of transport for utility purposes (Song et al 2017, cited Jones, 2012; Smith et al, 2011).

Steinback et al. (2011) finds a similar gender imbalance in a qualitative study which carried out 78 interviews of subjects with a range of demographics and levels of cycling experience in London, U.K. The qualitative research found that culture also played a part in choosing to cycle, with women feeling more self-conscious. In addition to gender, it was found that cycling was more popular with white males with higher salaries. Since publication in 2011, cycling has become a lot more visible in London, helped by the introduction of the cycle superhighways, so it may be that the gaps in perceptions between different groups of people may have narrowed, whilst the findings of this study remaining relevant to cities with lower cycling advocacy.

Table 1 below provides a summary of literature related to common barriers found with increasing the volume of cycling flows.

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Table 1. Literature Review of Cycling Research			
Author(s), Year, Location Title	Findings	Methods Used	Limitations / Implications / Future Research
Walta, 2018. International On the methodologies and transferability of bicycle research: A perspective from outside academia.	Different societies perceive cycling differently. New Infrastructure is most used in areas already high in cyclists	Literature review	Reconsider the application of methods rooted in the natural science approach. "It is more likely that a scientifically sound understanding of bicycle practice can be derived based on social science methodology."
Rossetti et al, 2017, Santiago, Chile I want to ride it where I like: measuring design preferences in cycling infrastructure.	Survey found that respondents either cycle every day or very rarely, not much in between. Experienced cyclists preferred on-street riding. Focus investment on areas non-commuters use as they are more likely to use it.	Stated-preference choice modelling study uses images of cycling infrastructure to investigate commuters' preferences. Snowball sampling technique over social media, starting with cycling advocacy groups.	Should be cautious when starting with cycling advocacy groups as they are not representative of all cyclists, never mind the general public.
Broach et al 2012. Portland, Oregon. U.S.A. Where do cyclists ride? A route choice model developed with revealed preference GPS data.	People willing to travel further to avoid busy un-signalled intersections and use segregated cycle paths. Painted cycle lanes alongside busy roads no more attractive than cycling on quieter street. But were valued when compared with busy roads without one. Regular cyclists are more likely to be male. Commute trips less sensitive to infrastructure, women and less-experienced cyclists prefer separated facilities.	GPS monitored route choice of 164 cyclists.	Sample largely made up of confident, regular cyclists and 80% male. For cycling rates to increase significantly, a wider range of people need to cycle, meaning the preferences of non-cyclists, occasional cyclists, and those who only ride for recreation but would consider cycling for transportation in different circumstances, including better infrastructure".

Andrade & Kagaya, 2012. Sapporo, Japan. Investigating behavior of active cyclists: Influences on bicycle commuting.	Owning a car has no influence on cycling. Respondents showed strong preference for sharing the pavement with pedestrians, as is the culture in Japan. As overall distance increased, bike-only trips decreased whereas multi-modal including bike increased as distance to public transport increased	Multi nominal logit model. Mailbox delivery, handing directly to cyclists, and online.	Mode splits have been derived from respondents, not representative of general population if handing out to cyclists. However, no statistical test was carried out to compare the sample with the general population.
Kircher, 2018. Linkoping, Sweden. Cyclist efficiency and its dependence on infrastructure and usual speed.	More formal infrastructure such as signals slowed *fast* cyclists down the most, whereas roundabout slowed *comfort* cyclists down the most as they chose to circle roundabout on pavement, giving way at each arm. Issue of red light for cyclists while green for parallel modes was raised.	GPS track, gaze direction, video study of cyclists with range of ability cycling through different junctions in Linkoping, Sweden.	Future Research: Willingness to cycle amongst mixed traffic. Limitations: small data set. Approximately 10 riders in each of the four competence groups.
Aldred et al, 2019. England. Barriers to investing in cycling: Stakeholder views from England.	Political barriers. Councillors and local councils fear cycle infrastructure would be unpopular, some anti-cycling themselves. Resource barriers. Lack of transport planners within councils, limited budgets, limited expertise, lead to poor schemes and negative perception by public. Suggested to raise spending per head to £10, then £20. (Netherlands spends £24 per head)	DfT Propensity to Cycle Tool can provide evidence for investment strategies. Maps cycling potential rather than existing levels. Useful as current levels are so low	Future Research: 1. Focused survey on local politicians, whose response rate was low within the original survey. 2. Survey sustainable transport practitioners to investigate more barriers to investing in different sustainable modes. 3. Include variables related to these barriers and enablers within models predicting infrastructure development and/or cycling uptake

Teschke et al, 2017. Montreal and Vancouver, Canada. Proximity to four bikeway types and neighborhood-level cycling mode share of male and female commuters.	Women appear to be put-off from cycling more than men where overall levels are low, but take-up cycling at equal rates once 7% mode share is reached. Connected networks, fewer slopes, close to bikeway all increase mode share. Non-linear relationship with distance.	Census level study, Montreal and Vancouver, Canada. Network created in GIS	Limitations of Study: Commute distance not recorded – only time. But distances covered more quickly on better more direct infrastructure. As data from Canada, time of year data collected (May) may have had an effect due to the influence of differences in weather on cycle flows.
Lovelace et al., 2017 England. The Propensity to Cycle Tool An open-source online system for sustainable transport planning.	Important to be in places of latent demand along desire lines, paper focuses on where rather than what to build. "*the shorter distances and more flexible routes that cycle paths can take increases the importance of high-resolution map-based tools for cycling compared with motorised modes*"	Tool for UK based research at a city-wide level. Route-based. (GPS data, O-D data). Can identify desire lines and potential or latent demand at each point in the network.	Future Research: 1. Create additional scenarios. 2. School commute routes focusing on safety. 3. Develop for new areas or countries.
Mertens and Van Dyck, 2016. Flanders, Belgium Which environmental factors most strongly influence a street's appeal for bicycle transport among adults? A conjoint study using manipulated photographs	Provide streets with cycle paths separated from motorised traffic because the type of cycle path by far is the most important. Safety was cited as biggest micro-environmental factor.	"Snowball Sampling" Web-based survey with photos showing different changes within the micro-environment (stated preference). 45-65 year-olds targeted. Images were photoshopped with different changes made to micro-environment.	Images look computer generated and limited to just one streetscape. Reveals preference not behaviours. Future Research: Survey different age groups to ensure respondents are more representative of the entire population.

Steinbach et al, 2011. London, England Cycling and the city: A case study of how gendered, ethnic and class identities can shape healthy transport choices	Cycling most popular amongst white, higher-earning males, citing benefits such as to health, autonomy and efficiency across London. However individual needs to be 'assertive' to defend against road danger and aggression. Identities of white male professionals bolstered by image of cycling, does not have same impact with lower class, black or Asian people, or women. Study found cycling had negative connotations within these ethnicities	Qualitative study that interviewed a range of people who did cycle, thinking about it, and who don't. Mix of jobs and demographics.	78 respondents of differing demographics. Can a valid profile of each age, sex, ethnicity, income level be determined on a handful of opinions? Disproportionate number of respondents are in cycling groups which leads to survey bias. The cycling infrastructure and culture in London has changed considerably since 2011, so likely no longer representative, but the issues are likely to remain relevant to smaller UK cities.
Branion-Calles et al., 2019. Canada & U.S.A. Associations between individual characteristics, availability of bicycle infrastructure, and city-wide safety perceptions of bicycling: A cross-sectional survey of bicyclists in 6 Canadian and U.S. cities	Only 57% feel safe when cycling and was the primary deterrent. In environments of low levels of cycling, older people and women are underrepresented, finding it less safe relatively. Found that with the introduction of cycling infrastructure encouraged some to cycle. Cyclists mostly male, educated beyond high school, no children, cycle 1-2 times a week. Non-white people tended to consider fewer routes as dangerous.	Weighted multinomial logistic regression was used to analyse the association between the availability of bicycling infrastructure and perceptions of bicycling safety	No data on the traffic volumes along each route. Future Research could track changes in safety perception before and after cycling network is expanded.

2.6 Effect of Teleworking on Pre-Pandemic Traffic

The trend of teleworking, which emerged long before the COVID-19 pandemic, leverages technology to enable working from locations other than the main site of employment, such as home. This shift, enabled by advancements in technology, holds the potential to significantly reduce commuting and business travel and therefore traffic congestion.

Nilles (1975) was one of the first to explore the concept of teleworking, or "telecommuting" and its potential to alter travel and land use patterns. By the late 20th century, it was shown that teleworking reduces the need to live close to city centres and allow people to live in more suburban areas without the need to commute large distances. The reduction in traffic would be particularly noticeable in the city centres, the destination of most commutes. On the other hand, it was identified that there could be potential for more traffic, as people move further out of the city to more car-dependent areas and contribute to urban sprawl they are more likely to use their car for other trips (Gareis & Kordey, 1999).

Nearly 20 years later, Moeckel (2017) (2017) agrees Gareis & Kordey (1999) that teleworking could lead to urban sprawl. By modelling changes in telecommunications in the city of Munich, they found that whilst teleworking reduced work-related trips, it increased non-work, longer trips outside the peak hours. This creates a fundamental shift in the time of day people travelled and the diurnal flow profiles of traffic.

Lila & Anjaneyulu (2017) also found reductions in travel time would be greatest in the peak hours when modelling Bangalore, India. They found telecommunications could reduce vehicle kilometres travelled by around 2-3% and vehicle hours travelled of 4-6%.

Giovanis (2018) found comparable traffic reductions. Using a linear study of Swiss household panel data between 2002-2013, they found telecommunications led to a 2% reduction in traffic. Another finding was that there was greater effect during bad weather, particularly when individuals' commutes were further and living in more isolated areas.

Overall, previous studies would suggest that an increase in teleworking can reduce the need to commute, reducing peak time traffic to a greater extent than non-peak.

Naturally, the reduction is seen more in employment areas such as city centres. On the other hand, teleworking has the potential to increase urban sprawl and the number of trips made for non-commuting purposes out of peak hours. It could be expected that work from home instructions during the pandemic would result in a large uptake of teleworking, seeing an acceleration of the trends outlined in this sub-section. If teleworking becomes much more common post-pandemic then these trends will remain in the long-term.

2.7 Travel and the COVID-19 Pandemic

Early academic research surrounding the COVID-19 pandemic studied the profound effect enforced lockdowns and fear of disease transmission had on travel behaviour and demand. As restrictions eased, focus switched to understanding the long-term implications to the post-pandemic period, often termed the “new-normal”. As disruptive as the height of the pandemic was, the new-normal will shape transport in the future and will therefore be of most interest to transport planners and be crucial to the efforts in reducing the impact of transport on climate change. This section will critically review literature across the pandemic and post-pandemic era. What is considered the ‘post-pandemic’ is subjective and differs across each country as each experienced diverse infection rates and governments took different approaches to managing the pandemic in terms of lockdowns and restrictions. Much of the academic literature in line with wider society consider the pandemic-era to have ended some time in 2021 or 2022, however the World Health Organization (WHO) only stated that COVID-19 no longer constitutes a “public health emergency of international concern” on the 5th May 2023 (WHO, 2023).

2.7.1 Change in Travel Demand during the Pandemic

It is widely accepted that travel is a derived demand, in the sense that the traveller is doing so for the utility gained at the destination. Therefore, if it is necessary on fewer occasions to travel to gain this utility, in theory this would result in less travel. Before considering individual modes, it is important to consider the impact of the pandemic on the overall necessity to travel in order to gain this utility. As discovered in the review of UK policy, the pandemic has accelerated the transition to WFH and flexible working arrangements, as well as online shopping, and understanding this is key to understanding why changes may have occurred post-pandemic.

Early research during or immediately after the pandemic often used online surveys to collect data, a logical choice considering lockdown prohibited in-person surveys. For example, Bick et al. (2021) uses an online national survey of 46,000 participants in the U.S.A. to track changes in commuting behaviour during the pandemic. They found that uptake in WFH was largest amongst people who solely WFH (rather than shifting to hybrid working), increasing from 7.6% of the workforce in February 2020 to 31.4% in May. However, this figure fell to 20.4% by the end of the year. The majority WFH-only increase was due to a shift in working patterns from employees who previously never WFH before the pandemic and were typically the higher educated. Conversely, those that shifted to solely WFH who already WFH on some days, pre-pandemic, returned to the same practices after the pandemic.

Whilst Bick et al. (2021) found higher levels of education increased the likelihood to WFH, Fatmi (2020) found higher incomes were associated with an increase in WFH practice in Kellowna, British Columbia, Canada. Overall, trips out of the house reduced by over 50%, with younger adults proportionately affected more. Ecke et al (2022) also found those with higher incomes and education levels were able to WFH more often consistent with Fatmi (2020). Moreover, the jobs that require working on site were not only less flexible in terms of location, but also had less scope for flexible working hours as they often followed shift patterns.

In Melbourne, Australia, Jain et al. (2022) also used an online questionnaire to gather data from 2,100 respondents between 26 June and 8 August 2020, finding a 310% increase in WFH during lockdown. Survey respondents indicated it could remain 75% higher in the post-pandemic period, however the paper states that data measuring actual behaviour shifts in the future would be valuable to compare with the self-reported findings in this study.

In addition to working practices, another aspect of society greatly impacted by COVID-19 lockdowns was shopping. During the pandemic, Echaniz et al. (2021) researched emerging transport patterns at the beginning of the pandemic across Spain. The two-week online survey beginning 9 April 2020 gathered 336 complete responses. One of the trends identified was that grocery shopping experienced an increase in online sales during the pandemic. People who did shop in person tended to do so less frequently and avoided larger hypermarkets. Worthy of reaffirmation is that the data was collected in April 2020 at the height of the pandemic and fear of infection was likely to be high at this point and therefore long-term assumptions based on this research cannot be made. Moreover, within the sample, young and old were underrepresented, whilst women overrepresented.

During and immediately after the pandemic, the only way for research to consider the post-pandemic period was to ask what the respondent intends to do in the proceeding years, as did Jain et al. (2022). Similarly, Adibfar et al. (2022) uses an online survey to create a discrete choice model with 206 respondents in Florida, U.S.A. Participants were asked in October 2020 about their behaviour in February 2020 (before the pandemic), September 2020 (during the pandemic) and how they expected they would behave in February 2021 (at the time a hypothetical 'post-pandemic' scenario). Consistent with Echaniz et al. (2021) findings in Spain, there was an increase in online shopping during the pandemic, however respondents showed signs of reverting to pre-pandemic habits, returning to in-store shopping. When considering the goods bought, grocery shopping remained in-store more than any other purchases during the pandemic. Respondents were more willing to shop for electronics, clothes and books online during the pandemic, however, whilst some people stated they will continue using online shopping for these goods, generally there is a desire to return to in-store shopping. Similar to other studies relying on online surveys, the sample sizes are fairly small, and the authors declare that the data set was not representative of the populations with young males being over-represented in this particular study.

Sometimes local context is needed when considering the impact that the pandemic may have had. Mogaji (2022) found it was not the will of the survey participants to adopt WFH and online shopping, but instead their perceived limitations associated with the local infrastructure. Mogaji (2022) organised semi-structured interviews across Nigeria, concluding that whilst commuters and shoppers desired a switch to online working and retail, they felt the local infrastructure would limit the potential.

2.7.2 Effect of the Pandemic on Vehicle Traffic

Emerging evidence internationally suggests that the change in WFH practice outlined in the previous sub section has created a shift in the frequency people commute, which is a contributing factor to the trend of reduced vehicle miles published by the DfT, shown in Figure 2.1. Prior to the pandemic, the number of vehicle miles travelled in Great Britain was growing annually from 2012, falling by 22% 2020 compared to

2019. The following two years have seen year on year growth of 12% and 9%, respectively, and are now at similar levels to 2016 levels (DfT, 2023b).

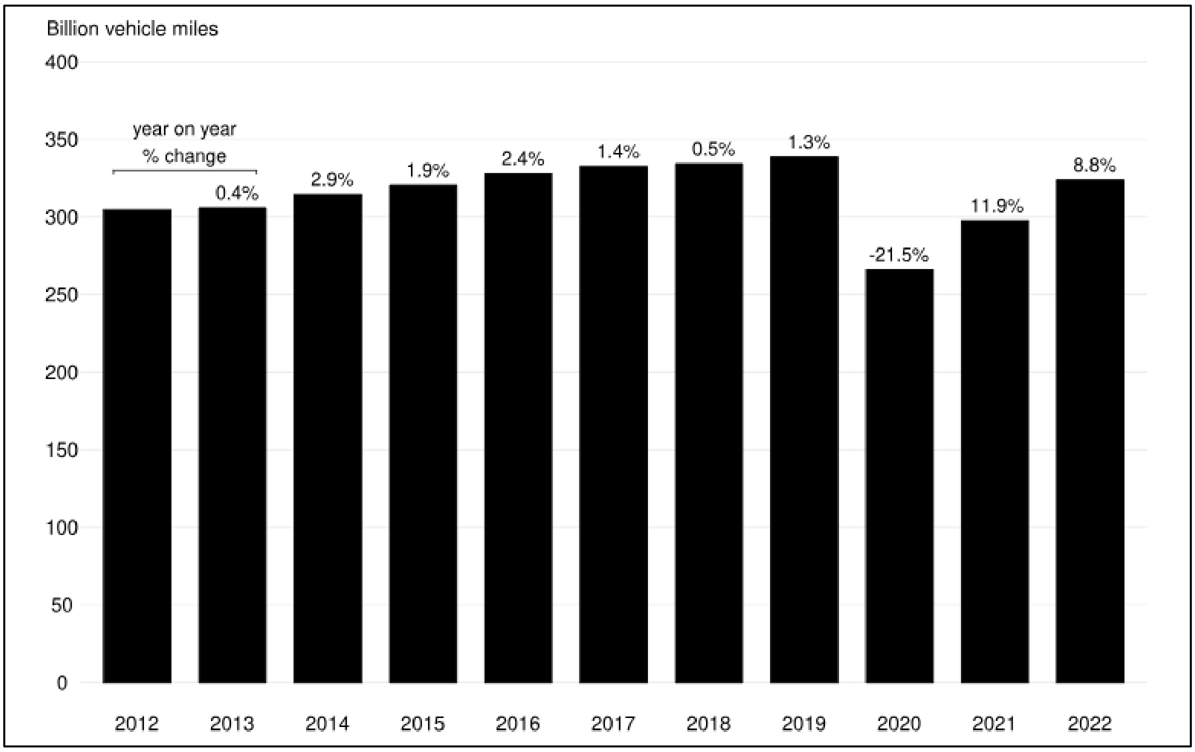

Figure 2.1. Vehicle miles travelled in Great Britain, 2012 - 2022 (DfT, 2023)

These figures indicate that road traffic is making a return to pre-pandemic levels in Great Britain, although absolute volumes only tell part of the story. The underlying changes in patterns of travel across the day are also important. This section will review academic research that identifies new emerging patterns in daily vehicle flows during and after the pandemic.

Ecke et al. (2022) researched panel data in Germany, which suggested that pre-pandemic patterns have been partially eradicated and new ones adopted though there remains uncertainty over long-term post-pandemic trends. They found that despite fewer people commuting by car during the beginning of the pandemic in 2020, there was no statistically significant change in the time of day they were commuting. However, as data was collected in the longitudinal survey German Mobility Panel, the findings are limited as the survey was carried out just as infections were increasing, and at the time no lockdown had been introduced in Germany.

In another study investigating the impact of the pandemic on commuting behaviour, Gao & Levinson (2022) whilst studying diurnal flow profiles captured by inductive loop detectors across six Californian cities (Sacramento, Oakland, San Francisco, San Jose, Los Angeles and San Diego) discovered that a dual-morning peak was emerging in the post-pandemic era. Cross-referencing with the California employment and household travel survey revealed that individuals who tended to previously commute in the middle of the A.M. peak (06:00h – 09:00h), worked in industries with greater ability to WFH or industries that witnessed a reduction in jobs during the pandemic. Reducing the demand to travel at that time resulted in the double-peak observed in the morning. The evening peak was measured between 16:00h and 19:00h, with less change experienced. Gao & Levinson (2022) state this is because there are more shopping and recreational trips occurring at the same time, lessening the effect of a change in commute practices on overall traffic flows. In terms of overall volume of traffic during the peak hours, it was found that after a sharp decrease in 2020, flows recovered in 2021 but did not reach the same levels of pre-pandemic volumes. Gao & Levinson (2022) state that this has led to reduced congestion in the cities and peak travel time has decreased. Whilst the paper does not state the implications that this will have on transport planning, a reduced demand to travel by vehicle may provide an opportunity to prioritise other, more sustainable modes of transport.

Consistent with Gao & Levison (2022), when studying vehicle travel speeds derived from GPS data in Hong Kong before and during the pandemic, Loo & Huang (2022) also found that the morning peak has been affected more than the evening peak. Reduced congestion on the roads was found during both peak hours, but particularly in the morning, which was attributed to increased WFH (Loo & Huang, 2022). They also found there was a spatial element to the reduction in congestion, with Hong Kong CBD seeing the greatest alleviation of traffic, suggesting the surrounding environment should be an important consideration when studying the impact of the pandemic. The authors considered the period of February – July 2021 as a "*new normal*" period, stating CBD peak hour congestion had returned. (Loo & Huang, 2022). suggest that for future study, volume of traffic rather than speed should be taken into consideration and that each day of the working week should be investigated to understand the post-pandemic.

As Loo & Huang (2022) recommend, Liu & Stern (2021) investigates the change in *volume* of traffic with changing severity of lockdown rules in Minnesota, U.S.A., with the aim to help to better understand how people react and therefore plan for future outbreaks or resurgences of COVID-19. Using detector data from January- July for

2015-2020, Liu & Stern (2021) found that motorised traffic reduced across the study area by 50%. Interestingly, when restrictions began to lift, the flows did not recover as expected, with the author concluding that WFH had continued beyond when it was mandatory.

Another finding in Liu & Stern (2021) was that specific days of the week were found to be affected more than others, with larger decreases at the end of the working week on Thursday and Friday, as well as the weekends due to less leisure facilities operating. However, by using daily total volumes, what Liu & Stern (2021) does not capture is the time of day these flows are occurring, which could provide additional insight into the changing travel patterns as a result of the pandemic, and specifically, the rise of working from home culture emerging afterwards. Moreover, the study does not go beyond July 2020, so it may be the case that flows continued to recover beyond the study period.

2.7.3 Cycling during the Pandemic

The increased cycling levels witnessed during the pandemic offers an opportunity to align recovery policies with the transition to net zero (Marsden & Docherty, 2021). The review of Transport Policy in Section 2.2 identifies that cycling has the potential to assist in achieving this. Whilst the number of miles cycled grew slightly between 2012 and 2019 in Great Britain, 2020, See Figure 2.2, the first year of the pandemic witnessed a substantial increase of 46% compared to the 2019 volume. This was followed by a decline of 21% in 2021 on 2020 levels, followed by a further decrease 7% in 2022 from 2021 levels, meaning that many of the additional miles cycled during the pandemic have already been lost (DfT, 2023b).

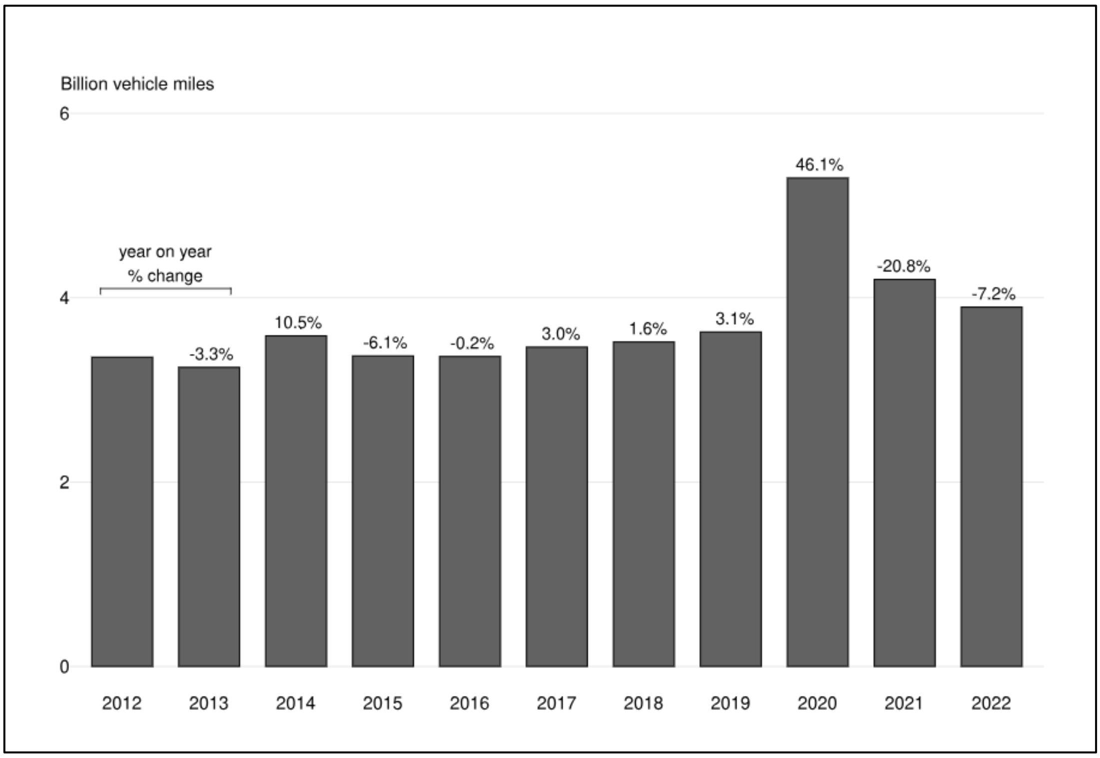

Figure 2.2. Pedal Cycle Miles in Great Britain, 2012 - 2022 (DfT, 2023)

Great Britain was not the only country experiencing an increase in cycling. Buehler & Pucher (2021) reviews data sources worldwide and analysed recorded cycle flows during the pandemic. It was found that in 11 EU countries (see list in Figure 2.3) there was an 8% in cycling during the pandemic. However, this was not distributed evenly between weekdays and weekends, with 3% and 23% increase on weekdays and weekends, respectively. Similar trends were witnessed in USA with a 16% overall increase (29% weekends and 10% weekdays) and Canada (3% overall increase, up 28% weekends and down 8% weekdays). The reduction in weekday cycling was likely due to decreases in travel to work, university, school and shopping because of restrictions. The permission to cycle as physical activity during the lockdown resulted in more recreational cycling, and the reason why it was proportionately more popular on weekends (Buehler & Pucher, 2021). Revisiting Eco-Counter data in 2023 shows that this trend is reversing, with the UK for example witnessing a 7% reduction in midweek cycling and 8% weekend cycling on 2022 levels, and 1% midweek and 2% weekend overall reductions considering all countries (Eco-Counter, 2023). Month by month fluctuations, which were localised and based on the lockdown conditions experienced in the specific city at the time, were found in both USA and European data. Therefore, it is important to consider the local lockdown conditions at the exact time the data is recorded (Buehler & Pucher, 2021).

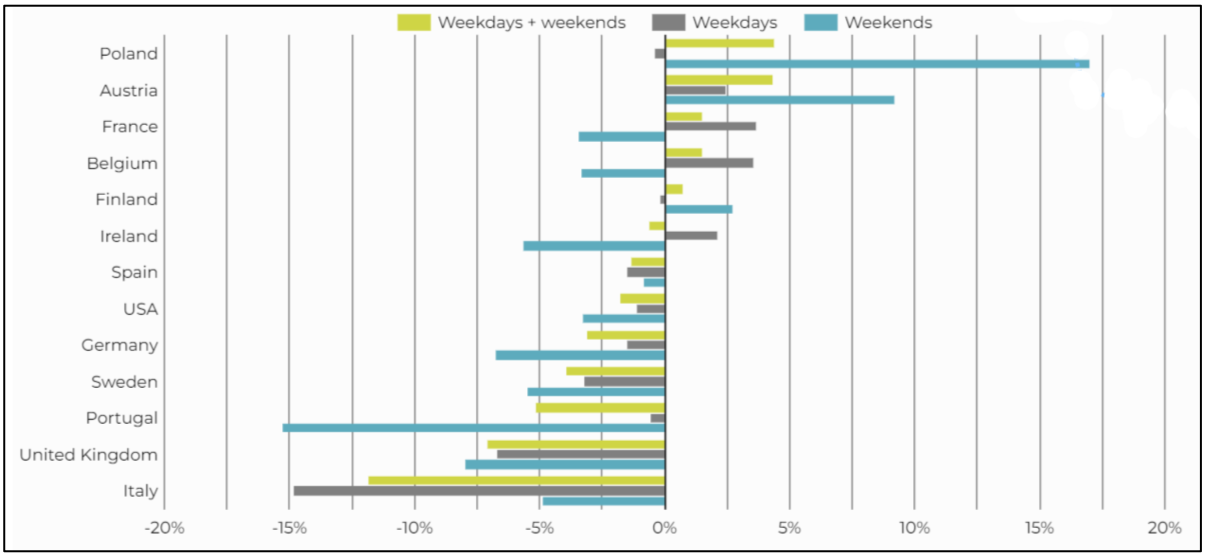

Figure 2.3 Cycling flows (Q1-Q3 2023 vs. Q1-Q3 2022) (Eco-Counter, 2023).

Buehler & Pucher (2021) also found that location is important when investigating changes in cycling volumes during the pandemic. Citing the findings from Streetlight, an app-based source of travel data, city centres in the USA reported declines in cycling volume, particularly on weekday peak mornings. Conversely, the largest increases were in the afternoon and early evening. Another US-based data provider, Rails-to-Trails, which coordinates walking as well as cycling use data on trails in the USA reported a 48% increase in 2020 on 2019 levels, supporting the theory that recreational trips make up the majority of the increase in cycle trips during the pandemic (Buehler & Pucher, 2021).

It may be misleading to observe changes in cycling flows in isolation without considering other modes and overall modifications to travel. Cities often reported increases in cycling as a proportion of total mode share. Examples include Vienna, up 2 percentage points from 7% to 9% between 2019 and 2020. The mode shift was even more substantial where infrastructure investment occurred. Where a protected cycle lane was introduced in Milan, the cycling mode share increased from 5% to 18% when comparing November 2020 with 2019. On the other side of the Atlantic, the USA experienced a 12% increase in cycling kms travelled, yet a 15% decrease in vehicle kms travelled. From February 2020 to January 2021, cycling fell by 28% in Bogota, Colombia, yet all travel except walking fell by 50%, meaning cycling mode share increased from 9 to 13%. (Buehler and Pucher, 2021 cited Streetlight, 2020)

Buehler & Pucher (2021) also analysed bike sales data and suggest that there is a likelihood cycling volumes will be maintained in later years due to substantial increases between 2019 and 2020. (+39% in the USA, +20% in Italy, +27% in France, +20% in the UK, +17% in Germany, and +23% in Australia). This could also be an indication that much of the increase in cycling during the pandemic was from people who did not previously own a bicycle, therefore could not cycle.

Conversely, (Cusack (2021) found in a survey of essential workers in Philadelphia, that the same demographic factors previously driving the propensity to cycle in the USA remained prevalent during the pandemic, with white people and those who are younger or males most likely to cycle. Having no children and living close to work were other significant factors. Even at a the time of a global pandemic, when vehicle numbers were much lower, safety concerns due to traffic were as important as the fear of infection of COVID-19 when travelling on public transport. Cusack (2021) recommends therefore that investing in infrastructure that protects cyclists from traffic is essential to encourage more people to switch modes. Cusack (2021) concludes that there needs to be more public engagement with infrastructure investment, which would reduce the potential for the poorly implemented infrastructure (Nikitas et al., 2021).

With respect to trends in recreational and commuter cycling during the pandemic (Hong et al., 2020) found similar patterns in the UK as Pucher & Buehler (2021). The study analysed cycle flows as the UK government-enforced policies restricted movement in the early stages of the COVID-19 pandemic in Glasgow, UK. It was found that in the early stages of the lockdown (up to April 20, 2020) cycling levels considerably increased due to non-commuting trips. Moreover, infrastructure type also influenced cycling volumes. Interestingly, it was recreational cycle routes that were already segregated from traffic that witnessed the biggest increase; however, while flows did increase, it might have been expected that on-road cycling would have benefited the most because road traffic substantially reduced. It was found that the expensive city centre-segregated infrastructure, which was a focus of policy pre-COVID-19, did not witness a significant increase in cycling volumes, possibly attributed to restriction on commuting affecting these locations most.

These studies provided useful insight into the initial impact of the pandemic, however there is a need to study beyond these periods of lockdown. Shi et al. (2023) studied the changes in the spatiotemporal use of the bike sharing in New York City, USA. By analysing data from two years pre-pandemic (2018 and 2019) and three years after the initial COVID-19 outbreak (2020 to 2022) the findings helped to develop an understanding of the long-term impact on human travel patterns, which is "*urgently needed*" to quote Shi et al. (2023). In addition to this, Shi et al. (2023) states that many previous studies divide dates into weekday-weekend, which ignores the actual characteristics of each day of the week, which may have changed significantly since the outbreak of COVID-19.

Shi et al. (2023) found that weekly temporal similarities with bike use emerged from the data within the three defined time periods: Pre-pandemic (2018 and 2019), pandemic (2020) and post-pandemic (2021 and 2022). The pre-pandemic can be defined by having a strong weekday-weekend divide with a spatial difference between distribution of commuting and recreational trips. The weekend-workday pattern disappeared during the pandemic and usage changed in line with the "*evolution of the pandemic*". During the pandemic, trips that began and ended at the same bike station increased and the authors suggested that these were likely to be non-commuting or utility trips.

An incidental finding regarding infrastructure provision was that inter-borough trips increased between Brooklyn and Manhattan in 2021 and 2022, at the same time a highway lane on the Brooklyn Bridge was converted to a bike lane, indicating the importance of investing in safe segregated infrastructure.

Shi et al. (2023) state that there has been a rebound in the post-pandemic to the pre-pandemic norm. However, no mention is made of the changes in the diurnal flow profiles during this time, even though they are presented in the results. By comparing 2019 average diurnal flow profiles (Shi et al., 2023, Figure 6) and 2022 (Shi et al., 2023, Figure 9), it is clear that the peak hours are less pronounced in the post pandemic than they were in the pre-pandemic, suggesting more consideration should be given to diurnal flow profiles in future studies. Whilst the absence of analysis of the diurnal flow profiles together with the emerging patterns that they potentially could have explained appears to have been missed by the author. A limitation that was stated within the study is that cycling cannot explain mobility as a whole and therefore multiple travel modes should be considered together.

It was not only transport researchers that were interested in the upsurge in cycling during the pandemic but also the medical professionals due to the potential health benefits of active travel, which has gained further recognition. Brooks et al. (2021)

suggest that COVID-19 has helped strengthen the social narrative that cycling is healthy not only from a social distancing context but also from reducing comorbidities that have increased the mortality rate within COVID-19 sufferers, this is applicable also, to other diseases. Laverty et al. (2020) conclude that transport has a profound impact on health and support of active travel following the end of lockdown will be crucial to ensure that the beneficial shift is maintained into the future. The previous research outlined in Section 2.5 states why it is important to maintain the increased cycling levels long after the pandemic and the need for evidence-seeking methods to better inform decision-makers. Therefore, developing a methodology that provides additional support to those implementing policies that promote cycling may help to avoid some of the negative consequences identified in pre-pandemic academic literature and popular press (McIntyre, 2021; Holland, 2021).

2.7.4 Active Travel Infrastructure Interventions during the COVID-19 Pandemic

The previous section has emphasised how the COVID-19 pandemic changed attitudes towards cycling, which became a much more popular choice of mode across the UK (Bicycle Association, 2020; Hong et al., 2020) and other parts of the world (Campisi et al., 2020; Lozzi et al., 2020). Walking, as another active travel mode, experienced similar traits to cycling. For example, (Nikiforiadis et al., 2022) studied walking activity before, during and after the pandemic in Greece, finding that after an initial increase in activity during the lockdown walking levels were returning to pre-pandemic levels in the respondent surveys.

These two active travel modes were often targeted together as many cities across the world reacted to the pandemic by expanding their walking and cycling infrastructure to provide for social distancing in the sustainable alternatives to public transport. There were over one thousand examples worldwide of local infrastructure interventions to support walking and cycling during the COVID-19 pandemic and documented within the open-access dataset created by (Combs & Pardo, 2021).

Many of the emergency plans to improve active travel facilities and restrict motorised vehicles were already part of long-term plans, however they were accelerated by COVID-19 which gained public and political support during the pandemic (Buehler & Pucher, 2021), something that has historically been a major stumbling block previously (Aldred et al., 2019).

The willingness and speed with which policies related to temporary infrastructure were acted upon has been linked with pre-COVID-19 advocacy for such facilities, particularly with cycling. In Italy, one of the first countries to experience high COVID-19 infection rates, cities with higher cycling advocacy such as Milan, Bologna and or Florence were found to react quicker to develop schemes that encouraged cycling during the pandemic whereas Palermo and Catania, which lack cycling lanes, were not as ready to implement measures (Barbarossa, 2020). Bogotá, Colombia, famous for the Ciclovía Movement, was one of the first cities to react by extending the already extensive cycle network by a further 76km introducing temporary lanes.

Buehler & Pucher (2021) surveyed 42 European and 200 cities from USA, finding 32 and 102 of them respectively expanded their cycling facilities in 2020. The largest increases were identified in New York (102km), London (100km), Montreal (88km) and Paris (80km). Kraus & Koch (2021) analysed 106 European cities with a total of over 1,200km of 'pop-up' temporary cycle infrastructure during the pandemic, finding an increase in cycling of between 11% and 48% in central areas, despite the uptake in WFH and closure of schools and universities.

Nikitas et al. (2021) provides an extensive review of case studies of temporary cycling interventions across the world during the pandemic. Unlike studies that investigated general trends across pre-existing infrastructure (Hong et al., 2020; Pucher & Buehler, 2021), cycling for both commuting and recreational uses in general were found to increase. Even at times of strict lockdowns when working from home was enforced, the significant reduction of commuting flows were more than compensated for by recreational and exercise trips. This was assisted with widespread adoption of temporary interventions such as traffic-calming measures and pop-up cycle lanes, demonstrating that they are feasible, and their use is important to continue to promote cycling. Being temporary and fast-tracked, there were some common issues; opposition from motorists, the aesthetics of the temporary infrastructure itself, and some ultimately failed to fulfil their purpose, such as appealing to commuters who ride regularly.

Dunning & Nurse (2020) argue that as a result of COVID-19, cities have discovered that their cycling networks can be rapidly expanded at low cost by reallocating space from motorised vehicles to cycles on already constructed roads. They state what is less clear is whether these interventions have occurred in the right locations. While one key strength of temporary infrastructure is that it can be modified or removed, Dunning & Nurse (2020) agree with Nikitas et al. (2021) that poor experimentation may result in a negative reaction in terms of both behaviour and attitudes toward future cycling infrastructure, as has been identified with schemes that predate the pandemic (Aldred et al., 2019). Planning new cycle infrastructure post pandemic will remain a "*complex process*" (Nikitas et al., 2021), and therefore, a greater understanding of the characteristics of cycling flows associated with a location on a route is a valuable input to the planning process. For example, investigating the diurnal cycle flow profiles reflects the trip purpose—whether they are mostly commuting or non-commuting. Whilst studies into the short-term impact of the pandemic, such as Hong et al. (2020), goes some way to addressing this uncertainty, understanding longer term impact of COVID on cycle and traffic levels is crucial to achieve active travel aspirations of the government.

2.8 Literature Review Summary

This chapter has identified the key areas for research and the opportunities presented to the transport sector as a result of the pandemic, which are summarised in Table 2. Following this, the key messages from academic literature and policy are brought together to identify the research gaps which has shaped the research questions for this thesis.

Table 2. Main Findings from Literature Review of the effect of the COVID-19 Pandemic on Transport

Main Topic	Sub-Topic	Findings	Example Studies
Changes to Travel Demand	WFH	Uptake and desire to maintain WFH practices remains in the post-pandemic.	Jain et al (2022), Bick et al (2021), Mogaji (2022)
	WFH	Higher-educated, high-income individuals more likely to be able to WFH.	Fatmi (2020), Bick et al (2021), Ecke (2022)
	Online Shopping	People are keen to return to shopping in-store, particularly when it comes to groceries.	Adibfar et al (2022), Echaniz et al, (2021)
Traffic flows	Return to pre-pandemic volumes	Traffic flows are returning-back to the pre-pandemic normal.	DfT (2023)
	Distribution of flows across the day	People have changed the time of day at which they travel in the post-pandemic.	Ecke (2022), Gao & Levins (2022), Loo & Huang (2022),
Active Travel	Walking during and after the pandemic	After a large increase during lockdown, walking volumes	Nikiforiadis et al. (2022)

		have returned to pre-pandemic levels.	
	Cycling during the pandemic	Rise in cycling trips during the lockdown.	Hong et al. (2020), Campisi et al. (2020), Lozzi et al. (2020), Shi et al (2023)
	Cycling post-pandemic	Volumes have decreased since the lockdown but remain higher than pre-pandemic levels.	Nikitas et al. (2021), (DfT, 2023), Bucher & Pueler (2021)
	Interventions to promote Active Travel	Interventions varied in success due to lack of time to plan.	Barbarossa (2020), Nikitas et al. (2021),
Public Transport	Levels of public transport patronage during lockdown	Public transport was hit particularly hard due to fear of infection as well as reduced travel demand.	Yang et al (2021), Echaniz et al, (2021), Ecke (2022)

Academics reacted quickly to the opportunity to research the effect of the pandemic on transport, however there are clearly limitations to research conducted during the early phase of the pandemic, and what can be learned from them (Akyelken & Hopkins, 2023). Many studies during the height of the COVID-19 pandemic used online surveys which struggled to attract a representative sample and rely on self-reported data. One of the key trends identified in the literature review was that people may have changed the time of day at which they travel in the post-pandemic, a research gap presenting itself to gain a deeper understanding of the extent that the diurnal flow profiles of both vehicles and active travel modes have changed, which will have implications to policy makers, transport modellers and planners. This gap, plus the other key finding that cycling had seen an unprecedented increase at the height of the COVID-19 pandemic, provided the basis for the first research question: *"What impact did the COVID-19 pandemic and resultant lockdown have on cycling volumes and diurnal flow profiles?*

This unprecedented increase in cycling during the pandemic that was detailed in Section 2.7.3. While the evidence of increased cycling during the pandemic is growing, there is limited understanding of whether these changes have persisted in the post-pandemic period. Buehler & Pucher (2021) and Shi et al. (2023) indicate initial increases in cycling, but for the purpose of meeting ambitious cycling targets set out in the policy reviewed in Section 2.2, there is a need to investigate if these trends have stabilised or reverted to pre-pandemic levels, leading to the research question: *"What are the longer-term impacts of the COVID-19 pandemic on cycling* *volumes and diurnal flow profiles, and to what extent can the post-pandemic period be called a 'new-normal'?*

Clearly there has been a barrier prior to the pandemic and there is a need to know why there was such a suppressed demand for cycling preventing these higher numbers of cyclists during the pandemic (Section 2.5). it was found that the overarching, most significant barrier is a lack of safe infrastructure segregated from vehicles. The COVID-19 pandemic, reduced vehicle traffic and the EATF provided opportunity to analyse cycling flows segregated from traffic. However, whilst the rapid implementation of temporary active travel infrastructure during the pandemic through the EATF provided a unique opportunity to promote cycling and walking, the success and long-term impact of these interventions remain unclear. Studies by Nikitas et al. (2021) and Dunning & Nurse (2020) highlight the potential benefits and challenges, but more detailed analysis is needed to determine the effectiveness of these measures in sustaining increased active travel. Moreover, most studies have focused on individual modes of transport in isolation, resulting in a research gap for modes to be studied in parallel. By investigating walking and cycling together, it will provide a more comprehensive understanding of the overall impact of the EATF schemes. Therefore, the following question was asked: *"Did cycling and walking flows change in the post-pandemic period in locations where active travel infrastructure interventions occurred during the pandemic?"*

The transport sector has been aware of the negative externalities associated with urban transport for much of the previous century. A review of seminal papers from the literature from Tripp (1942), Buchanan (1963) and Banister (2005) suggest that privately-owned vehicle trips are the cause of many of these and therefore volumes of which need to decrease in favour of a modal shift towards more sustainable modes such as public transport or active travel.

With this in mind, a review of the UK Transport policy published since the pandemic suggests that the increase in working from home and online shopping has changed the amount of traffic on the roads. Additionally, flexible working patterns may have led to a spreading of flows over the day, lessening the impact of the peak period. Research into the pandemic period by Gao & Levinson (2022) and Loo & Huang (2022) backs these statements up, finding a lessening of peak travel times, but a research gap is present to understand whether these shifts will prevail longer into the post-pandemic, leading to the research question: *"How have the change in vehicle flow volumes and diurnal flow profiles differed to those of cycling between the pre-pandemic and post-pandemic era?".*

The literature review has highlighted several key research gaps that need to be addressed to understand the long-term impacts of the COVID-19 pandemic on travel patterns. The next chapter, the methodological review, will outline the research design and methods that will be employed to address the research questions derived from the research gaps.

Chapter 3. Methodological Review

3.1 Introduction

The previous chapter has highlighted the importance of understanding the changes in the spread of travel across the day in the post-pandemic era, not only for daily traffic flow volumes but also simultaneously for active travel. Moreover, much of the research surrounding travel changes due to the pandemic was largely restricted to online surveys that struggled to collect representative samples. Both motorised modes of transport and active travel have experienced a fundamental change in diurnal traffic flow profiles, with the latter identified as an area of interest for carbon emission saving potential. Implications of these changes will affect the assessment and planning of transport systems, as well as informing decision makers of the fundamental shifts in travel patterns across different modes. Taking this into consideration, this chapter reviews the appropriateness of using time series data clustering to examine these fundamental changes in a quantitative manner, eliminating the issue of bias introduced in many of the previous studies. Section 3.2 defines diurnal traffic flow profiles and 3.3 provides an overview of how they can be analysed. This is followed by a critical review of literature that use cluster analysis to identify their underlying patterns (Section 3.4). Section 3.5 details the data preparation stages before the different methods of clustering are reviewed in Section 3.6. Finally, the chapter is concluded in Section 3.7.

3.2 Diurnal traffic Flow Profiles

Traffic flow volumes are typically recorded as a time series, defined as "*a collection of observations made sequentially through time*" (Chatfield, 2004). Being a stochastic process, flows often follow patterns that allow future observations to be predicted to some degree. Unlike other types of data, calculating the mean and standard deviation of a time series data does little to describe such characteristics.

Most traffic flows are diurnal, meaning they possess a pattern that that occurs over a day. Flows may also display a weekly pattern. It is often assumed that working days, usually Monday to Friday, behave differently to the weekend (Saturday to Sunday) and in some cases Sunday may be different from Saturday. There is also seasonal variation, the severity of which differs according to location and mode of transport.

Ideally, flows are compared across the entire year to factor in seasonal changes, which takes significant time to collect data for. In addition to these factors there is some random variation that can be attributed to events, breakdown, collisions, weather conditions or emergency road works. As traffic is generated by human activity, this generates a great deal of randomness too (Jiang et al., 2003).

Despite the predictable nature of traffic and active travel flows, the previous chapter highlighted how the pandemic has brought about changes in peoples' travel behaviour, meaning it can no longer be assumed that pre-pandemic patterns are representative of current temporal patterns in daily flows. The following section will explore the possible methods to investigate these changes.

3.3 Methods to Investigate Changes to Diurnal Flow Profiles

As stated in Chapter 2, early research into changes to travel during the COVID-19 lockdowns used online surveys (Fatmi, 2020; Bick et al., 2021; Jain et al., 2022), a limitation of which was that they often resulted in respondent samples that were not representative of the wider populations (Akyelken & Hopkins, 2023). Moreover, questionnaire surveys are known to have other limitations. For example, a reliance on self-reporting raises concern about the validity of the results for (Razavi, 2001). Additionally, factors such as small convenience samples, recall bias, and the inability to validate self-reported data, potentially made even more difficult during isolation during the lockdown periods, further undermine the accuracy of the results (Remillard et al., 2014). In contrast, a quantitative approach, incorporating observed data sources could provide a stronger foundation for understanding the true impact of the pandemic on travel patterns.

Alternatively, time series data is commonly analysed with models such as Autoregressive (AR), Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA). Whilst prior to the pandemic these models often accurately forecast future observations, problems arise with the presence of structural breaks (or level changes), large amounts of anomalies or outliers and significant changes in seasonal and trend patterns (Peña et al., 2001). As discussed in Section 2.7, the COVID-19 pandemic created fundamental changes to travel patterns, particularly during the height of lockdown, that may produce such conditions.

Structural breaks occur when there is an abrupt change in the mean or other parameter in the data, such as during the COVID-19 lockdown when vehicle traffic drastically reduced and cycling increased. See Section 1.6 for a detailed breakdown of each COVID-19 pandemic stage that likely resulted in a structural break to the time series data.

Secondly, as explained in the previous section, traffic flows exhibit daily, weekly, seasonal and annual trends that could be predicted to some extent prior to the pandemic. The drastic changes caused by the pandemic and shift to flexible working disrupted these patterns, and things may not ever regress to pre-pandemic conditions. To compound these issues, seasonal patterns require several years' worth of data, however there has not been sufficient time post-pandemic to train a time series model.

Finally, the pandemic era is almost certain to contain substantially more outliers and anomalies than the pre-pandemic era, such as sudden drops in transport usage during lockdowns or spikes as restrictions were lifted. These anomalies can distort the estimation of AR, MA, and ARIMA models, contributing further to poor forecasts and misleading inferences when using pre-COVID data.

What is required is a methodology that does not rely on extensive homogonous, predictable historical data. Cluster analysis of time series is a less common method to investigate traffic flow data. Whilst it is not as powerful as the likes of ARIMA for forecasting future flows, it has the potential to be more appropriate for exploratory analysis as it can be used to understand underlying patterns in data without making strong assumptions prior to the analysis, nor is it restricted by any of the issues described in this section brought about by the COVID-19 pandemic.

The next section will discuss how data clustering can be applied to the diurnal flow profiles of multi-modal travel modes to investigate how they have changed a year on from the COVID-19 lockdown.

3.4 Case studies using Clustering of Diurnal Flow Profiles

Time series clustering has been used in a wide range of fields, including economics, the natural environment and built environment (Montero & Vilar, 2015; Maharaj et al., 2019). Clustering is an unsupervised machine learning task (Chung, 2003; Azimi & Zhang, 2010) that aims to group similar, unlabelled objects together.

Early research using clustering for traffic data analysis largely focused on categorising the traffic state at a given time for short-term predictions, usually on a highway (Jiang et al., 2003; Deng et al., 2009; Azimi & Zhang, 2010), and whilst these studies adopted similar clustering methodologies as studies considering traffic data as a time series, the shape of the diurnal flow profile is of less concern for the purpose of their research. Studies that focus on the shape of the diurnal flow profile tend to be more interested in longer term planning of transport systems. For example, Vogel et al. (2011) is an early example that deviates from motorised vehicle counts. Understanding the diurnal flow profiles of a bike-sharing system better informs the strategic, long-term planning of the locations and size of the stations, improved planning at this stage leads to less intervention at the mid-term (e.g. invest in convenient drop-off locations and incentivise use) and at the operational level from the provider (e.g. manual re-distribution of the bikes across the network).

When focusing on traffic data in a time series format, motorised traffic remains the most common mode of transport as the subject of clustering, however, there has been a growing interest in more sustainable modes, including walking (Li & Xu, 2021; Hernández-Vega et al., 2021), bike sharing, as mentioned earlier, (Vogel et al., 2011) and light rail (Vidal et al., 2022). An overview of previous studies that utilise cluster analysis on flows of various modes can be found in Table 3.

Table 3. Summary of literature on clustering of traffic flows

Author(s), Year, Title	Study Details	Objectives & Clustering Method	Findings & Limitations
Niemeier *et. al.* (2002) Cluster Analysis for Optimal Sampling of Traffic Count Data: Air Quality Example	Central California, USA Flow Profile Motorised Traffic 53 sites 4-year period Hourly flows	**Objectives** Cluster to improve diurnal daily traffic flow profiles in air quality model without the need to use more permanent counters. **Method** Disaggregated normalised data by time of day, day of week and location, Hierarchical, Complete-Linkage, Pearson Correlation.	**Findings** Average hourly diurnal flow profiles for one site are a good substitute for another site in the same cluster, Crucial to the methodology is the quantity of historical data. **Limitations and Future Study** Day split into three time periods before clustering rather than using diurnal profile.
Chung (2003) Classification of Travel Pattern	Tokyo, Japan Traffic State Motorised traffic 1 Site 2-year period 16 element wavelets	**Objectives** To apply different clustering algorithms to understand the nature of traffic conditions for short-term travel time predictions. **Method** Partitional 'small-large ratio' clustering of two six-hour periods after dynamic wavelet transformation.	**Findings** Travel times in AM (7am-1pm) period could be classified into weekday, Saturday and Sunday periods. PM (3pm-9pm) did not produce distinguishable patterns. **Limitations and Future Study** Does not take into account the shape of the curve in the clustering, or the month (seasonal factors).
Jiang *et. al.* (2003) The Study on the application of Fuzzy Clustering Analysis in the dynamic identification of road traffic state	China (City not specified) Traffic State Motorised Traffic 15 Sites 1-week period 2-minute intervals	**Objectives** Applying clustering to identify the state of road traffic. **Method** Fuzzy k-means Clustering using sum of squared differences of microwave sensor data where state of traffic conditions is measured using volume, speed and lane occupancy.	**Findings** Traffic is also qualitative in nature; people have perceptions of what is busy etc. The fuzzy clustering allows for a more qualitative approach to describing the cluster memberships.

Author(s), Year, Title	Study Details	Objectives & Clustering Method	Findings & Limitations
Weijermars and van Berkum (2005) Analyzing highway flow patterns using cluster analysis	Apeldoorn, Netherlands Flow Profile Motorised Traffic One Site 15-minute intervals One-year sporadically	**Objectives** Develop method to improve macroscopic traffic models. Imputation of missing data. **Method** Ward's hierarchical method using Euclidean distance, pre-classified working and non-working days.	**Findings** Clustering observations proved more effective than by features. Pre-classifying into working and non-working days reaped better results, with work days possessing more recurrent traffic patterns. **Limitations and Future Study** Seasonal variation is not considered, only one site and the pre-classification of days occurred pre-COVID, capturing temporal trends throughout the week is important in post-pandemic trend analysis.
Thomas *et. al.* (2008) Variations in urban traffic volumes	Almelo, Netherlands Flow Profile Motorised Traffic 30-minute intervals One-year period 20 intersections	**Objectives** Clustering to identify anomalies from a sample to exclude. **Method** Ward's hierarchical clustering, Euclidean distance. Unsupervised.	**Findings** Clustering was able to identify anomalies effectively. **Limitations and Future Study** No analysis was conducted on the diurnal flows that were identified as anomalies. Other future study could involve data from city that experiences congestion, unlike Almelo.
Deng *et. al.* (2009) Real-time freeway traffic state estimation based on cluster analysis and multiclass support vector machine	Los Angeles, California USA Traffic State Motorised Traffic Five-day study period Two-minute intervals	**Objectives** To convert real-time traffic data into traffic states. **Method** Model created from partitional k-means using square of Euclidean norm on historical traffic state data. Input real-time data to identify real-time traffic state.	**Findings** The model is over 95% accurate on the test data. This indicates that the method is an effective way to solve the traffic state estimation problem. **Limitations and Future Study** Only one site analysed over a five-day period. Future study could test the model with data from another road and time period.
Azimi and Zhang (2010) Categorizing Freeway Flow Conditions by Using Clustering Methods	Austin, Texas, USA Traffic State Motorised Traffic One site 15-minute intervals 11-month study period	**Objectives** To test different clustering methods to classify freeway traffic flow conditions on the basis of flow characteristics, then compare with Highway Capacity Manual (HCM). **Method** Six-cluster solution tested for k-means, Fuzzy c-means and CLARA methods.	**Findings** Results support current practice the HCM's density-based level-of-service criterion for uncongested flow. However, clustering provided a means of reasonably categorising oversaturated flow conditions, which the HCM is currently unable to do. K-means performed the best.

Author(s), Year, Title	Study Details	Objectives & Clustering Method	Findings & Limitations
Vogel *et. al.* (2011) Understanding bike-sharing systems using data mining: Exploring activity patterns	Vienna, Austria Flow Profile Bike-share 63 Sites 2-year period Hourly flows	**Objectives** Analyse bike-share station use patterns to inform management of distribution of bikes. **Method** Normalised flows, Expectation Maximisation, Euclidean distance.	**Findings** Five distinct flow profiles across scheme. Exploratory evidence that clusters could be linked to spatial proximity. **Limitations** 2 years of data aggregated to three flow profiles per site, lot of temporal detail lost (day of week, seasonality).
Soriguera (2012) Deriving traffic flow patterns from historical data	Barcelona, Spain Flow Profile Motorised Traffic 14 Sites on one road 5-year period	**Objectives** To derive detailed long-term patterns from hourly traffic volumes to support planning and operational decisions. **Method** Normalised flows from toll booth data Hierarchical using average within group linkage, Euclidean distance.	**Findings** Cluster analysis performed better than typical ad-hoc, subjective practises. Three-step also outperformed simple k-means. **Limitations and Further Study** Does not compare three-step process results with standard hierarchical clustering. Further study could adapt to other datasets such as O-D matrix or Add traffic state data into the clustering.
Guardiola and Mellor (2014) A functional approach to monitor and recognize patterns of daily traffic profiles	Minneapolis, Minnesota, USA Flow Profile Motorised traffic 1 site 7-year period	**Objectives** Develop a methodology for dimension reduction of time series data before clustering. **Method** Partitioning Around Medoids using outputs of principle component analysis.	**Findings** Flows at 7am and to a lesser extent 3-5pm were driving the principal component scores and thus the clustering. **Limitations and Further Study** Functional data could be used in a regression model to estimate traffic profiles.

Author(s), Year, Title	Study Details	Objectives & Clustering Method	Findings & Limitations
Necular (2015) Analyzing traffic patterns on street segments based on GPS data using R	New Haven, Connecticut, USA Flow Profile Motorised traffic Hourly flows 5,330 ‘segments’	**Objectives** Identify contiguous set of road segments and time intervals that form traffic patterns. **Method** k-means of normalised, aggregated flows extracted from GPS traces.	**Findings** Clustering in R has good data mining capabilities. Shopping and recreational activities have a unique temporal usage pattern. **Limitations and Further Study** Day-to-day variations ignored as at each site flows aggregated to an average Weekday, Saturday and Sunday flow profile. Future study could apply methodology to other data source, e.g. loop detectors.
Li and Xu (2021) The Impact of COVID-19 on Pedestrian Flow Patterns in Urban POIs—An Example from Beijing	Beijing, China Flow Profile Pedestrians Hourly flows 997 sites One-month period	**Objectives** To understand and identify whether some points of interest share similar pedestrian flow profiles to aid enforcement and lifting of pandemic restrictions. **Method** Disaggregated data by stage of pandemic, k-means on raw data. Geospatial subjective analysis based on points of interest in proximity to sites	**Findings** More variation in pedestrian flows after lockdown (4 clusters immediately before lockdown, 2 during 3-week lockdown, 6 immediately after). Proximity to different points of interest impacted the clustering results. **Limitations and Further Study** Volume dictates clustering as flows not normalised. Only goes one month beyond lockdown, and there were subsequent lockdowns after data collected so not true reflection of post-pandemic era. Future study should analyse data over a longer time period
Jimenez and Vega (2021) Clustering Approach to Generate Pedestrian Traffic Pattern Groups: An Exploratory Analysis	Guadalupe, Costa Rica Flow Profile Pedestrians Up to 60 days per site Hourly flows 46 Sites	**Objectives** To establish distinct diurnal flow profiles through clustering. Explore the influence of proximity to various services on flow profiles. **Method** Hierarchical Ward’s method using Euclidean distance. Flow profiles aggregated to create average working day per site. Influence of proximity to key services were analysed	**Findings** Pedestrian flows were highest around mid-day in Guadalupe CBD. There was no statistically significant pattern with proximity to services but may be due to several being close to each counter site. **Limitations and Future Study** No determining variability between weekdays as all aggregated to one average flow, which reduces the number of unique flow profiles to cluster. Opportunity for further exploration of the geospatial elements.

Author(s), Year, Title	Study Details	Objectives & Clustering Method	Findings & Limitations
Song and Yang (2021) Clustering and understanding traffic flow patterns of large-scale urban roads	Qingdao, China 15-min intervals One-month period Motorised traffic 464 sites	**Objectives** To identify traffic flow patterns by clustering two-dimensional vectors that contain geospatial and temporal data. **Method** K-means clustering using Euclidean and Mahalanobis distance on two-dimensional vectors (flow profile and geospatial).	**Findings** Clustering generated four main groups based on morning-peaks, evening-peaks, morning and evening peaks, and no peak flow profiles. **Limitations and Future Study** Went to great lengths to cluster based on points of interest, but unable to present any findings.
Vidal *et. al.* (2022) Point-Process Modeling and Divergence Measures Applied to the Characterization of Passenger Flow Patterns of a Metro System	Valparaíso, Chile Modelled Flow Profile Metro arrivals 20 stations One-month period Hourly flows	**Objectives** To Characterise flow patterns between Metro stations. **Method** Cluster outputs of Gaussian mixture intensity function with both hierarchical and partitional methods (k-medoid).	**Findings** Silhouette coefficient suggests two clusters optimal solution, study uses five to ensure different flow profiles in the analysis. Further evidence that it is a subjective process. **Limitations and Future Study** Paper dedicates a lot of time to explaining Gaussian mixture intensity function, a complicated extra step that is not necessary if clustering every diurnal flow profile rather than aggregating to one per site with confidence intervals etc. Only looks at Tuesdays with Aug 2019. Little discussion about flow profiles.

3.5 Data

Clustering is a flexible tool which means there is more than one way to prepare the data prior to the main analysis. Sections 3.5.1 – 3.5.5 provide a critical review of the data preparation stages when undertaking cluster analysis, including the collection, aggregation, pre-classification, and normalisation of the data. The use of observations, features and modelling outputs derived from the time series also will be explored.

3.5.1 Data Collection Sources

Any data collection method that records the volume of traffic, or travellers, within a time series vector can be analysed using clustering. A conventional data source is from stationary points on the road network, usually recorded by inductive loop (Weijermars & van Berkum, 2005; Thomas et al., 2008) detectors. Loop detectors use a coil of wire embedded in the road and when a vehicle (metal box) cuts the associated magnetic field the detector measures the change in inductance. Whilst inductive loops are useful for monitoring vehicles and cycles (metal frame and wheels) they are unsuitable for measuring pedestrian flows However, the diversity of data sources from emerging technologies is expanding, increasing the availability of transport data. Necula (2015) uses GPS traces from a smart phone app in New Haven, USA whilst Vidal et al. (2022) uses an Origin-Destination, OD, matrix derived from model outputs for the Metro system in Valparaíso, Chile and Soriguera (2012) uses data from toll booths in Barcelona, Spain. Emerging technologies offer the most benefit counting pedestrian flows, which cannot be recorded with the traditional approach of fitting inductive loop detectors. Examples of studies utilising emerging technology to analyse pedestrian flows include Hernández-Vega et al. (2021) who use counters that possess passive infrared sensor and high-precision lens to count pedestrians in Guadalupe, Costa Rica and Li & Xu (2021) use pedestrian densities across 200m^2 areas of Beijing.

3.5.2 Data Aggregation

When processing temporal patterns in traffic flow time series data, there has to be a compromise with the time intervals to which the traffic counts are aggregated. If the time period is too small, flow profiles will not be smooth and possess fluctuations, if too large, important details of the profile may be lost (Vogel et al., 2011).

Often this decision is taken out of the hands of the researcher as traffic counts are typically aggregated over hourly time periods to reduce the data storage requirements (Soriguera, 2012). This is reflected in the findings from the review of previous literature (Figure 3.1), which shows seven of the sixteen studies use flows aggregated to 60 minutes. The studies that used flows aggregated to five minutes (Jiang et al., 2003; Chung, 2003; Deng et al., 2009; Zhang et al., 2022) focussed on analysing the traffic state in the short-term for congestion prediction, rather than long-term traffic profiles for traffic or air quality modelling.

15, 30 and 60 minutes appear to be the common aggregation time periods. Whilst there is risk anything above 60 minutes risk missing key characteristics of the flow profile, anything less than 15 minutes is likely to require additional steps before clustering, for example dynamic time warping to ensure key trends in the profiles map on to one another if not perfectly aligned temporally; or smoothing using moving averages to avoid the aforementioned fluctuations in the data.

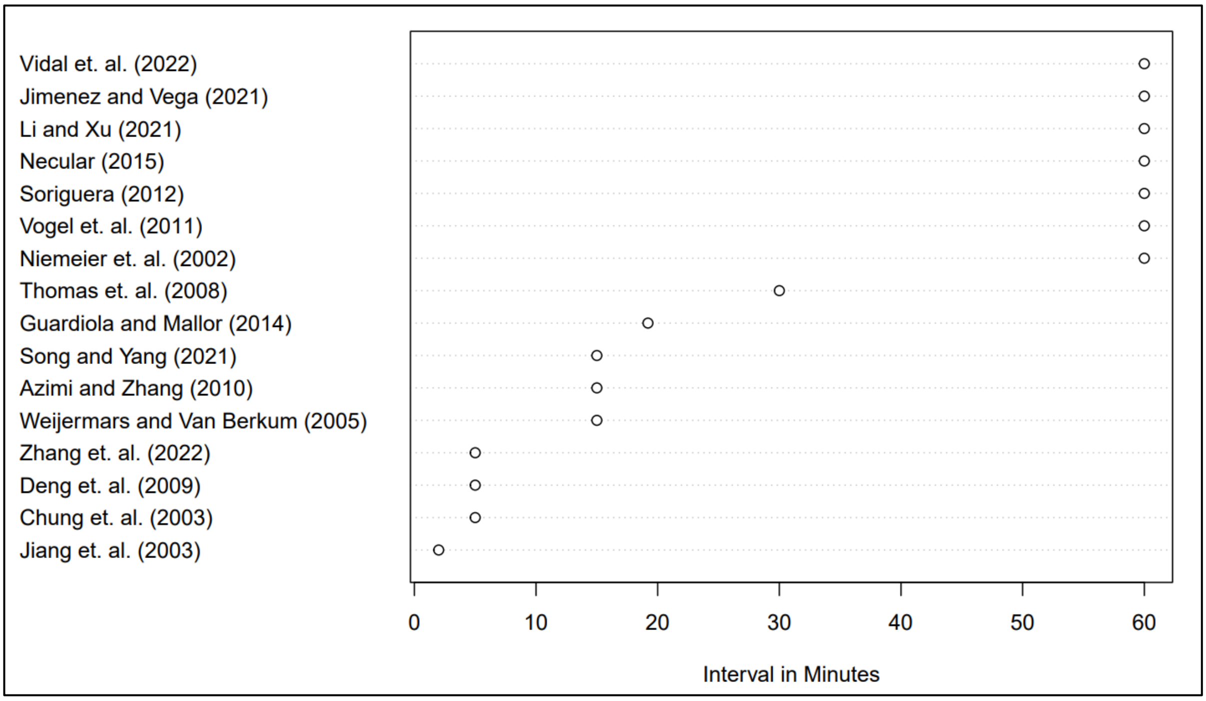

Figure 3.1. Review of traffic count data aggregation by clustering study

With reference to Figure 3.1, (Guardiola et al. (2014) cluster with 75 splines across the day which equates to one every 19.2 minutes, however, the raw data that generated the splines was initially aggregated to two-minute intervals.

Whilst traffic counts are aggregated over specific time intervals across the day, they also can be aggregated by taking the average values over several similar days to create one flow profile. Necula (2015) weighs up the pros and cons of aggregating data across several weeks based on five intervals – 1) Mondays, 2) Tuesday – Thursday, 3) Friday, 4) Sat and 5) Sun, compared with three intervals; 1) Monday – Friday, 2) Saturday and 3) Sunday. Ultimately, they decided on aggregating to the three intervals across the week as the reduction in the variance from the five-day solution negligible. The three time periods were fused together to create a time series with 72 attributes, 24 for each of the time period, as shown in Figure 3.2. By clustering according to the shape of the time series created this way, the five working days of Monday to Friday contribute 1/3 of the clustering procedure, whilst Saturday and Sunday each contribute 1/3. This creates an unbalanced weighting towards the weekend days and likely give them a disproportionate impact on the finalised clustering of sites.

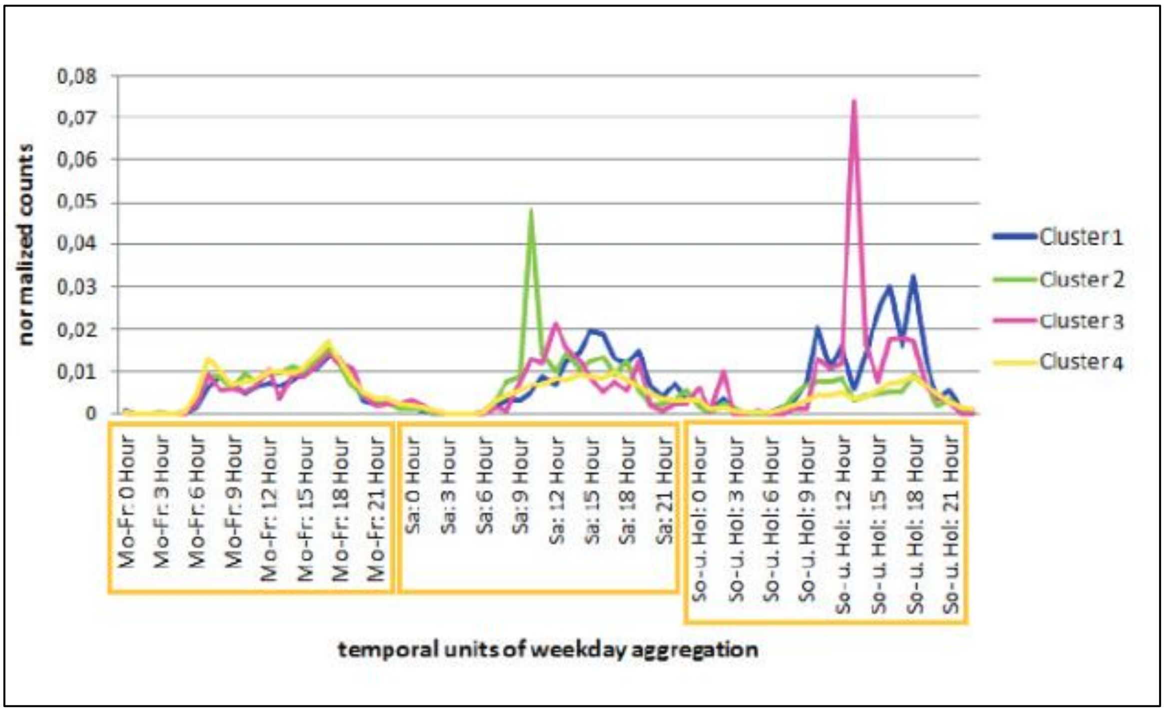

Figure 3.2. Necular (2015). 72-hour time series representing full week.

Like Necula (2015), Vogel et al. (2011) also aggregated flows over the hour whilst using the average values over the study period to create one time series per site.

The difference in Vogel et al. (2011) approach is that each day of the week is represented, creating a time series with 168 elements (24 hours x 7 days), as shown in Figure 3.3.

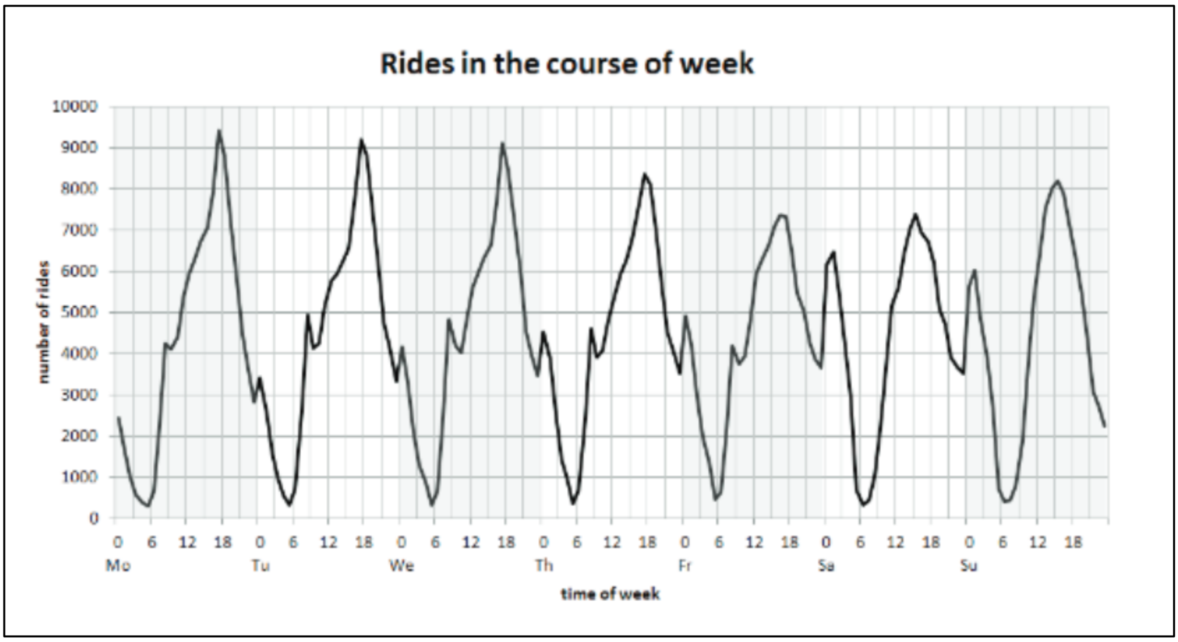

Figure 3.3. Vogel (2011) 168-hour time series representing full week.

By aggregating the data to a time series that represents the entire week, the patterns relating to the specific day of the week are less likely to be detected by the clustering algorithm than if they were clustered over a diurnal period as is the case in most other studies. Moreover, by taking one average flow profile per site rather than clustering with each individual day removes the opportunity for inter-day variation due to changes in people's travel choices to be analysed, for example when considering the impact of different seasons, or during an event such as a lockdown stage in the pandemic.

3.5.3 Pre-Classification

Similar to the aggregation dilemma, there is the option to pre-classify data prior to clustering and this can be achieved in various ways. Whilst pre-classification reduces the 'unsupervised' aspect of data clustering, it may be necessary if the objective is to reduce variation within the dataset to enable tighter, more representative clusters to form, as patterns in road traffic for example can be predictable based on the day of the week they are occurring (Crawford et al., 2017). Weijermars & van Berkum (2005) compares results *before* and *after* classifying the diurnal traffic flows into working and non-working days. It was found that the variation within clusters pre-classification was “quite large” and found after classifying produced more acceptable results. However, Weijermars & van Berkum (2005) acknowledged that by pre-classifying there is the potential to miss underlying patterns in the data. Given this statement was made in the context of traffic flows before the pandemic, pre-classifying diurnal flows is inappropriate when investigating temporal patterns in traffic flows during the pandemic which is an aim of this study. The variation in diurnal flow profiles is due to the uncertainty of travel patterns during and since the pandemic raising questions such as: What days do people work from home? Do people commute at different times on different days of the week?

3.5.4 Observations, features, and model outputs

Once the data is collected, the observations (raw flows) can be clustered as they are, features can be generated based on the observations, or observations can be fed into a model before clustering the outputs. Guardiola et al. (2014) uses functional data analysis to generate features that represent the time series vector in a reduced dimension whereas Vidal et al. (2022) is an example of cluster-based modelling.

However, observation-based clustering is the most direct approach and is particularly useful and even recommended when the aim is to identify similar geometric profiles (Maharaj et al., 2019). Weijermars and van Berkum (2005) is a seminal piece of work that compares clustering results when using observations and a two-step feature-based method, finding the observation approach yielded better results. Given the aim of this study is to identify patterns in flow profiles, observation-based clustering is not only the most straight-forward, and thus more likely transferable, but possibly the most appropriate and therefore will be the method used. For the purpose of this review, methodologies that have applied normalisation and / or aggregation to the data are still regarded as observation-based, as the time series structure of the data remains intact.

3.5.5 Normalisation

The primary objective of the clustering process is to group daily flows according to the shape of their diurnal flow profile irrespective of the magnitude. In other words, a factor that has to be considered when performing a single cluster analysis on the flows of multiple sites is that the total flow volumes will differ across sites, as some inevitably will be used more than others, for example, if it was required to cluster diurnal flows from an arterial dual-carriageway and a residential access road in the same dataset. Without normalisation, the formation of the clusters would be dominated by the total volume at each site.

Li & Xu (2021) is an example of a study that does not normalise the time series data before clustering. The result is that the cluster memberships are often decided by the flow volume at each site, as they are the main driver of dissimilarity. At one site in particular, the airport, the pedestrian flows are so much greater than elsewhere and they formed a cluster on their own, irrespective of the shape of the diurnal flow profile.

However, most previous studies have used normalisation to ensure the shape of the daily flow profiles drives the cluster memberships and not the total volume, with the most common practice being to divide the hourly flow by the total flow for that day (Niemeier et al., 2002; Vogel et al., 2011; Necula, 2015; Hernández-Vega et al., 2021). Soriguera (2012) takes a slightly different approach by dividing the hourly flow by the average hourly flow for the day.

Based on these studies, equation 3.1 below is an expression that normalises the data and also zero centres the data:

$$N_t = \frac{q_t - \bar{q}_t}{\bar{q}_t} \tag{3.1}$$

Where,

N_t = normalised cycle count for each consecutive hour t, separately for each of the 24 hours across a day

q_t
= actual measured cycle count for each consecutive hour t, separately for each of the 24 hours across a day

$\bar{q}_t$ = mean hourly count averaged over the 24 hours across a day

Where $\bar{q}_t = \frac{\sum_{t=1}^{24} q_t}{24}$

By definition it follows that $\sum_{t=1}^{24} N_t = 0$.

Another approach is standard scores, or z-scores. Although has not been used in transport time series studies is common in other fields to neglect the absolute values within a time series (Möller-Levet et al., 2003; Liao, 2005). When raw, or observation-based time series clustering is performed it usually involves a scale transformation, with z-standardisation used in the *"vast majority of cases"* (Delforge et al., 2021). For example, Z-scores were found to produce "fair" results when forecasting stock exchange time series (Bhanja & Das, 2018) whilst Delforge et al. (2021) found z-scores outperformed raw data when investigating time series clustering approaches within the field of applied geophysics. See equation 3.2 below.

$$Z_t = \frac{x_t - \mu_t}{\sigma_t} \tag{3.2}$$

Where,

Z_t = standardised count for each consecutive hour t, separately for each of the 24 hours across a day

x_t = measured count for each consecutive hour t, separately for each of the 24 hours across a day

μ_t = mean hourly count averaged over the 24 hours across a day = $\mu_t = \frac{\sum_{t=1}^{24} x_t}{24}$

σ_t = standard deviation of the hourly count over the 24 hours across the day = $\sigma_t = \sqrt{\frac{\sum_{t=1}^{24} (x_t - \mu_t)^2}{24}}$

By definition it follows that:

$$\sum_{t=1}^{24} Z_t = 0$$

Normalisation scales data to a fixed range, while standardisation scales data to have a mean of 0 and a standard deviation of 1. This typically means that z-standardisation is better suited to datasets with more variability than normalising around the mean (Nicholson et al., 2022).

3.6 Review of Clustering Methods Used

Once the appropriate data set has been sourced and pre-processed as required, whether it be observation-based, feature-based or modelled outputs, there are two further decisions to make when determining the clustering methodology; 1) how will the similarity between vectors (each diurnal flow profile) be determined and 2) what variant of hierarchical or partitional clustering will be used. Sections 3.6.1-3.6.5 provide an overview of these factors.

3.6.1 Hierarchical clustering

Hierarchical clustering partitions the data step-by-step based on their similarity, either from the whole data set containing all *n* individuals through to *n* clusters each containing only one individual (divisive), or vice versa (agglomerative). Of the two, agglomerative is the most commonly used. Hierarchical clustering produces a dendrogram that can be used to inform the number of clusters into which to group data, something that cannot be achieved with partitional methods and as a result cited as one of the reasons studies have proceeded with hierarchical (Weijermars & van Berkum, 2005; Soriguera, 2012). Another key property of hierarchical methods to consider is that once the division, or fusion, has been made, it is irreversible. Hawkins et al. (1982) states that in some datasets this is not an issue. In fields such as taxonomy, where data naturally has a hierarchical structure, i.e. one level of classification of species in the hierarchy is a sub-group of the one above. However, this is not the case for all data and Hawkins et al. (1982) demonstrates this problem by considering the following eight individuals of single measurements:

$$-2.2, -2, -1.8, -0.1, 0.1, 1.8, 2, 2.2.$$

Hawkins et al. (1982) states that there are clearly three clusters within the dataset. With a divisive hierarchical clustering method, the ‘central’ cluster (-0.1 and 0.1) would be split in the first division, leaving a two-cluster solution of -2.2, -2, -1.8, -0.1 and 0.1, 1.8, 2, 2.2. In the next division into three clusters, it is not possible to reunite the central cluster. From a diurnal traffic flow context, the same problem can be illustrated as in Figure 3.4.

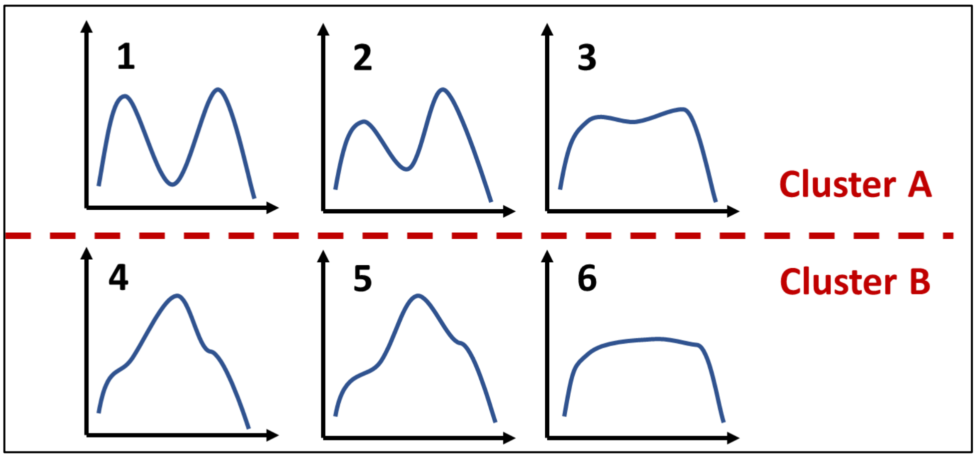

Figure 3.4. Illustration of issue with divisive hierarchical cluster analysis in a traffic flow context

Where the y axis represents flow volume and the x axis time, the first division into Cluster 'A' and 'B' could potentially separate flows 3 and 6 when reducing the variance within each cluster, despite the two likely forming their own cluster in a three-cluster solution, with 1 & 2 and 4 & 5 forming the other two. If adopting the hierarchical method, this is something of which to be cautious.

Notwithstanding, examples of traffic flow profile studies that use hierarchical clustering include (Niemeier et al., 2002; Weijermars & Van Berkum, 2005; Thomas et al., 2008; Soriguera, 2012; Hernández-Vega et al., 2021). How the clusters form in hierarchical cluster analysis based on the dissimilarity values is decided by the clustering methods, outlined in Table 4.

Table 4. Standard agglomerative hierarchical clustering methods. Source: adapted from (Everitt et al., 2011)

Method	Usually used with	Distance between defined as	Remarks
Single linkage	Similarity or distance	Minimum distance between pair of objects, one in one cluster, one in the other	Produces unbalanced and straggly clusters (chaining), particularly in large data sets. Does not take account of cluster structure
Complete linkage	Similarity or distance	Maximum distance between pair of objects, one in one cluster, one in the other	Finds compact clusters with equal diameters (maximum distance between objects)
(Group) Average linkage	Similarity or distance	Average distance between pair of objects, one in one cluster, one in the other	Joins clusters with small variances. Intermediate between single and complete. Takes account of cluster structure and is relatively robust
Ward's Method (Average Within)	Distance (raw data)	Increase in sum of squares within clusters, after fusion, summed over all variables	Assumes points can be represented in Euclidean space for geometrical representation. Tends to find same-size, spherical clusters. Sensitive to outliers

3.6.2 Partitional clustering

Whilst hierarchical clustering performs incremental divisions or merges of clusters, partitional methods do not follow this hierarchical structure. In most cases, partitional clustering aims to minimise the within group variability. Of the partitional methods, k-means is the most popular within traffic flow studies and in general (Maharaj et al., 2019), one benefit of which is their ability to compute high dimensional data (Berkhin, 2006).

Transport studies that use partitional clustering methods include (Chung, 2003; Jiang et al., 2003; Deng et al., 2009; Guardiola et al., 2014; Necula, 2015; Li & Xu, 2021; Song & Yang, 2021; Vidal et al., 2022). Most use k-means but examples of different methods include Vidal et al. (2021) that uses k-medoid and Jiang et al. (2003) that uses fuzzy k-means.

k-means, also known as c-means, seeks an optimal partition of the data by minimising the sum-of-squared error. From a diurnal flow profile perspective, k-means achieve this through the following broad steps:

1. Generate an initial partition of the data randomly, calculating the 'cluster prototypes' (centroids or means) of each cluster;
2. Assign each flow profile to the nearest cluster centroid based on a distance measure;
3. Recalculate the cluster prototypes with the assigned flow profiles.
4. Repeat steps 2 and 3 until there is no improvement in the cluster solution.

Mathematically, this is shown in the equation 3.3 below taken from Maharaj et al. (2019).

$$min\colon \sum_{i=1}^{I} \sum_{c=1}^{C} u_{ic} \; d_{ic}^{2} = \sum_{i=1}^{I} \sum_{c=1}^{C} u_{ic} \; ||\mathbf{x}_i - h_c||^2,$$

$$\sum_{i=1}^{C} u_{ic} = 1, u_{ic} \geq 0, u_{ic} = \{0,1\} \qquad (3.3)$$

Where:

u_{ic} indicates the membership degree of the i-th unit to the c-th cluster; $u_{ic} = \{0,1\}$, that is, $u_{ic} = 1$ when the the i-th unit belongs to the c-th cluster, $u_{ic} = 0$ otherwise.

$d_{ic}^2 = |\mathbf{x}_i - h_c|^2$ indicates the squared Euclidean distance between the i-th object and the centroid of the c-th cluster.

Example of studies include Necula (2015) who opts for k-means clustering after comparing results with hierarchical and the density-based spatial clustering of applications with noise (DBSCAN). They found determining the number of clusters within hierarchical-based method was “ambiguous”, likely referring to the cutting of the dendrogram, whereas the DBSCAN produced uninterpretable results due to either too many clusters or too few. Unlike k-means, DBSCAN struggles with high-dimensional space (Everitt et al., 2011), as is created when clustering time series, as well as clusters with varying density.

Where k-means uses the centroid of each cluster, which is the geometric centre, or mean position of the cluster, Partitioning Around the Mean (PAM), otherwise known as k-medoids, uses an observation that is the most representative of the cluster, the medoid. This is useful when the data cannot be represented by a mean value, such as when clustering images, however diurnal flow profiles typically can be represented by the mean flows.

3.6.3 Computational effort of k-means and Hierarchical Clustering

Clustering diurnal flow profiles can require a large amount of computational effort as time series tend to be high-dimensional. For example, if using hourly flow counts, one diurnal flow profile will require 24 variables, one for each hour of the day. Therefore, computational capability can be a limiting factor when analysing big datasets.

Because of this, previous research has determined which of the clustering algorithms require the least computational effort. Both Karthikeyan et al. (2020) and Gupta et al. (2021) conducted a comparative study to determine the best-suited algorithm between k-means and agglomerative hierarchical clustering, finding that k-means is best used for larger datasets with minimal runtime and memory change rate. Ghosh & Dubey (2013) found that introducing fuzzy-based c-means required a longer computational time when compared to conventional centroid-based k-means.

Sharma et al. (2012) found k-means was the simplest and fastest clustering algorithm when compared with DBSCAN, Expectation Maximisation, ‘Farthest First’, and ‘Ordering Points to Identify the Clustering Structure’, or OPTICS, and therefore the most appropriate to be used with large datasets.

Whilst hierarchical clustering has advantages, particularly not needing to pre-define the number of clusters, k-means may be necessary when dealing with larger datasets due to its lower computational demand.

3.6.4 Dissimilarity factors

After selecting either hierarchical or partitional methods, it is necessary to quantify the difference between the diurnal flow profiles (Montero & Vilar, 2015). As traffic flows are continuous, proximities between individuals are typically quantified by dissimilarity measures (Everitt et al., 2011), whereas for categorical data, measures of ‘similarity’ are used. Dissimilarity measures can be broadly divided into distance measures and correlation-type measures.

Euclidean Distance and other distance-based methods

Distance measures can be used to evaluate one-to-one mapping of pairs of vectors, such as diurnal traffic flow profiles when the objective is to compare profiles of time series (Montero and Vilar, 2015). The distance measure most commonly used is the Euclidean distance (Everitt et al., 2011), which can be expressed as shown in equation 3.4:

$$d_{ij} = \left[\sum_{k=1}^{p}\left(x_{ik} - x_{jk}\right)^2\right]^{\frac{1}{2}} \tag{3.4}$$

Where x_{ik} and x_{jk} are, respectively, the $k\mathrm{th}$ value of the $p\text{-dimensional}$ observations for individuals i and j. This distance has the appealing property that the d_{ij} can be interpreted as physical distances between two $p\text{-dimensional}$ points $\mathbf{x}_i' = (x_{i1}, \dots x_{ip})$ and $\mathbf{x}_j' = (x_{j1}, \dots x_{jp})$ in Euclidean space. Formally this distance is known as the l_2 norm” (Everitt et al., 2011).

The city block distance, otherwise known as the Manhattan distance, describes distances in a rectilinear configuration and derives its name from the grid-like street layout of its namesake. Both the Euclidean and City Block distances are special cases of the Minkowski distance. See Everitt et al. (2011) for detailed descriptions of each distance-based dissimilarity measure in more detail.

Pearson and other correlation-based distances

Correlation-based dissimilarity measures have the potential to be suitable for time series applications. Critics of correlation coefficients state that they are generated by standardising data by row (i.e. the individual) rather than by column (the variables) in the data matrix (Everitt et al., 2011). Mean values and variance within variables are therefore not usable. This also nullifies the effect of magnitude to some extent. Everitt (2011) uses the example of x_i'= (1, 2, 3) and x_j'= (3, 6, 9) having a correlation of $\emptyset_{ij} = 1$, thus not deeming the two dissimilar and negating the fact that x_j' is three times larger than x_i'. Rather than being a disadvantage this could be used beneficially to ensure that it is the shape of the diurnal traffic flow profiles driving the clustering process rather than the volumes. The use of correlation coefficients can be justified in this case when variables are measured on the same scale, as traffic volumes are, and the values recorded are “only to provide information about the subject’s relative profile” (Everitt et al., 2011), as is the objective of this study.

The use of correlation-based dissimilarity is less common than distance-based in the traffic flow profile literature, however Niemeier et al. (2002) adopts Pearson correlation as the dissimilarity measure as opposed to the more common distance-based approaches. Niemeier et al. (2002) states Pearson correlation is used to identify locations across Central California that share similar patterns in flow profile rather than the absolute volumes. Pearson correlation coefficient can range from -1 to 1, where 0 in the case of traffic flow profiles indicates that two sites share no correlation and a coefficient of 1 between flow profiles suggests the shape of one site can be predicted exactly with the shape of another. Niemeier et al. (2002) explains Pearson correlation can be expressed as equation 3.5 for traffic flow profiles.

$$r_{(j,k)} = \frac{\sum_i (P_{i,j} - \overline{P_j})(P_{i,k} - \overline{P_k})}{\sqrt{\sum_i (P_{i,j} - \overline{P_j})^2 \cdot \sum_i (P_{i,k} - \overline{P_k})^2}}$$

(3.5)

Where;

P_{ij}= average proportion of traffic at hour i and count location j,

$\bar{P}_j$ represents the average of the $P_{i,j}$ over the *h* hours, for count location j.

Niemeier et al (2002) sets a minimum of 0.9 for the correlation coefficient before individuals or clusters are able to merge with one another. Complete linkage hierarchical method is used. The flow profiles are firstly disaggregated to similar geographic areas within central California, then are aggregated to one average profile per site, with the day being split into three time periods (03:00h – 11:00h, 11:00h – 16:00h, 16:00h – 21:00h), meaning the variance is reduced sufficiently to allow the relatively high minimum value of 0.9 correlation to be selected. Niemeier et al. (2002) states that any lower and each flow profile within a given cluster would not be sufficiently representative of another, any stricter and there would be no clusters of significant size to draw any meaningful conclusions. At 0.9, five of the 16 clusters contain just one site's flow profile at the specific time period and geographic region presented as an example in the results section. Niemeier et al. (2002) is only interested in finding sites that are similar to one another so the first step in their analysis is to ignore those five clusters, whereas for the research within this thesis, all clusters are to be considered.

3.6.5 Determining the number of clusters

Li & Xu (2021), Vogel et al. (2011) and Vidal et al. (2022) use the Silhouette coefficient amongst other indices to assess the goodness of fit of the cluster solution and identify the optimal number of clusters for the solution. The gap statistic, and within sum of squares (WSS) are other methods to determine the similarities within and differences between clusters.

Weijermars & van Berkum (2005) plots the variation within clusters as a scree plot to find at which number of clusters the 'elbow' lies, or the point at which an increase in cluster numbers does not have a significant decrease in the sum of within cluster variation across the entire dataset. It was found that five clusters over working days and four over non-working days was the optimal solution, with working days forming closer knit clusters of the two. This was found by Weijermars & van Berkum (2005) to work far better than not pre-classifying as the largest variance is filtered out in this stage.

Necula (2015) assesses results based on two to eight clusters. Any higher than eight and the author assumes they become more difficult to provide meaningful insights as they become too niche. A four-cluster solution is chosen based on a “goodness-of-fit” plot, just one less than Weijermars & van Berkum (2005) and also is able to interpret the results in a concise manner due to the smaller number of profiles to analyse. During the working days, peaks in the traffic were clearly visible between 06:00h-07:00h, 12:00h-14:00h and 16:00h-17:00h, corresponding with going to work, lunch, and leaving work, respectively. However, despite Necula (2015) assuming weekdays are similar, the results suggest there is a high level of variation within the weekday flows and this has generated a smoothing effect of the average diurnal flow profiles for each cluster. This suggests that the aggregation of weekdays into one 24-hour profile before being fused to Saturday and Sunday, as illustrated in Figure 3.2, is perhaps not ideal. However, one finding was that average profiles over the weekend segments of the fused time series correspond to different activities, for example one cluster corresponds with the opening times of retail whilst another cluster is associated with the hospitality sector, with a late-afternoon peak for dinner time.

Vidal et al. (2022) decides to use five clusters, despite the Silhouette coefficient suggesting that a two-cluster solution was optimal. This was justified to allow more diurnal profile shapes to be identified across the Valparaíso metro system being analysed.

In the study of a Vienna bike share scheme, Vogel et al. (2011) found five clusters to be the optimal solution The benefit of a smaller number of clusters such as five is that the shapes can be interpreted and labelled. Typical diurnal profile shapes were distinguishable by sites where more bikes were picked up in the morning than the evening, another cluster demonstrated the opposite, one cluster was defined by higher activity during night, one during mid-day, and the final cluster with no distinguishable features, resembling the mean average of all other clusters.

Choosing the number of clusters is a subjective process, and whilst Vogel et al. (2011) chooses the five-cluster solution, perhaps a four-cluster would remove the cluster Vogel deemed 'average'. Conversely, the variation in this cluster could be explored, and if it was larger than the other clusters, a six-cluster solution could break this cluster up.

3.6.6 Factoring in geospatial elements

Arbitrary links between the temporal elements of flow profiles and geospatial factors of the locations were recorded are made in previous studies but they are far from conclusive (Necula, 2015; Song & Yang, 2021; Jimenez & Vega, 2021; Li & Xu, 2021). Vogel et al. (2011) identifies a potential link with geospatial and temporal elements of traffic flow profiles but acknowledges it is just exploratory analysis and additional research into the geospatial factors driving the relationship would need to be studied in the future.

3.6.7 Diurnal flow profile clustering during the COVID-19 pandemic

Li & Xu (2021) is the only example of clustering diurnal flow profiles in relation the COVID-19 pandemic, albeit over too short of a time period to provide insight into the post-pandemic era. Limitations aside, the k-means clustering of pedestrian flows in Beijing before, during and immediately after the first lockdown of society provided an interesting finding that pre-pandemic, the optimal number of clusters in the solution was four, this reduced to two during the pandemic when movement was restricted but increased to six after the pandemic. This suggests that immediately after the restrictions were lifted, people were travelling at different times of the day and not returning to the pre-pandemic norm. Another caveat that needs to be applied to any of Li & Xu's (2021) findings is that the flows were not normalised and therefore total flow volumes at sites were dictating the clustering.

3.7 Methodological Review Summary

This chapter has critically reviewed each step of data clustering as a methodological approach to investigate changes within diurnal flow profiles as a result of the COVID-19 pandemic. A review of the data collection and preparation stage revealed diurnal flows aggregated to hourly counts were a common and effective data source. Whilst previous studies tended to pre-classify data into working and non-working days, this approach would fail to reveal emerging trends in the post-pandemic across the working week, and the opportunity to identify a new-norm missed. Observations are the simplest and optimal choice to cluster rather than using model outputs or features of the observations and normalising is important if using more than one site.

Reviewing the clustering methods themselves revealed both hierarchical and k-means were popular options. Determining the number of clusters is a subjective task but can be aided by measures such as the WSS and silhouette profile.

The next chapter will detail the methodological approach taken for the three studies that has been developed through the understanding gained from the critical review of literature explored in this chapter.

Chapter 4. Methodological Framework

4.1 Introduction

The previous chapter critically reviewed a wide range of methodological approaches to clustering diurnal profiles which have been applied predominantly to a range of sources of motorised traffic flow data. The gap in the research identified was the lack of multi-modal study, particularly that includes non-motorised traffic. Due to the COVID-19 pandemic being so recent, evidence from clustering flow profiles in the post-pandemic is also much needed. Confident that clustering of diurnal flows is the appropriate statistical approach to address the aims and objectives set out in Chapter 1 the methodology for the research is set out in this chapter.

The research comprises three studies of diurnal flows at different stages of the COVID-19 pandemic up to the end of 2022. The approaches common to all three studies are explained in this chapter, whilst details of methods, analysis and findings specific to the data of the individual studies are covered in their respective chapters that follow.

This chapter, with reference to the flow diagram in Figure 4.1, outlines the methodological framework and structure of the later chapters of this thesis. All studies use data from Tyne and Wear, in the North East region of England, UK, which will be introduced in Section 4.2. The acquisition of data for the study will be discussed in Section 4.3 before describing the common data preparation steps that all three studies share in Section 4.4. Section 4.5 is a critical discussion on the suitability of data, the choice of software for clustering is discussed in Section 4.6 before the chapter is concluded in Section 4.7.

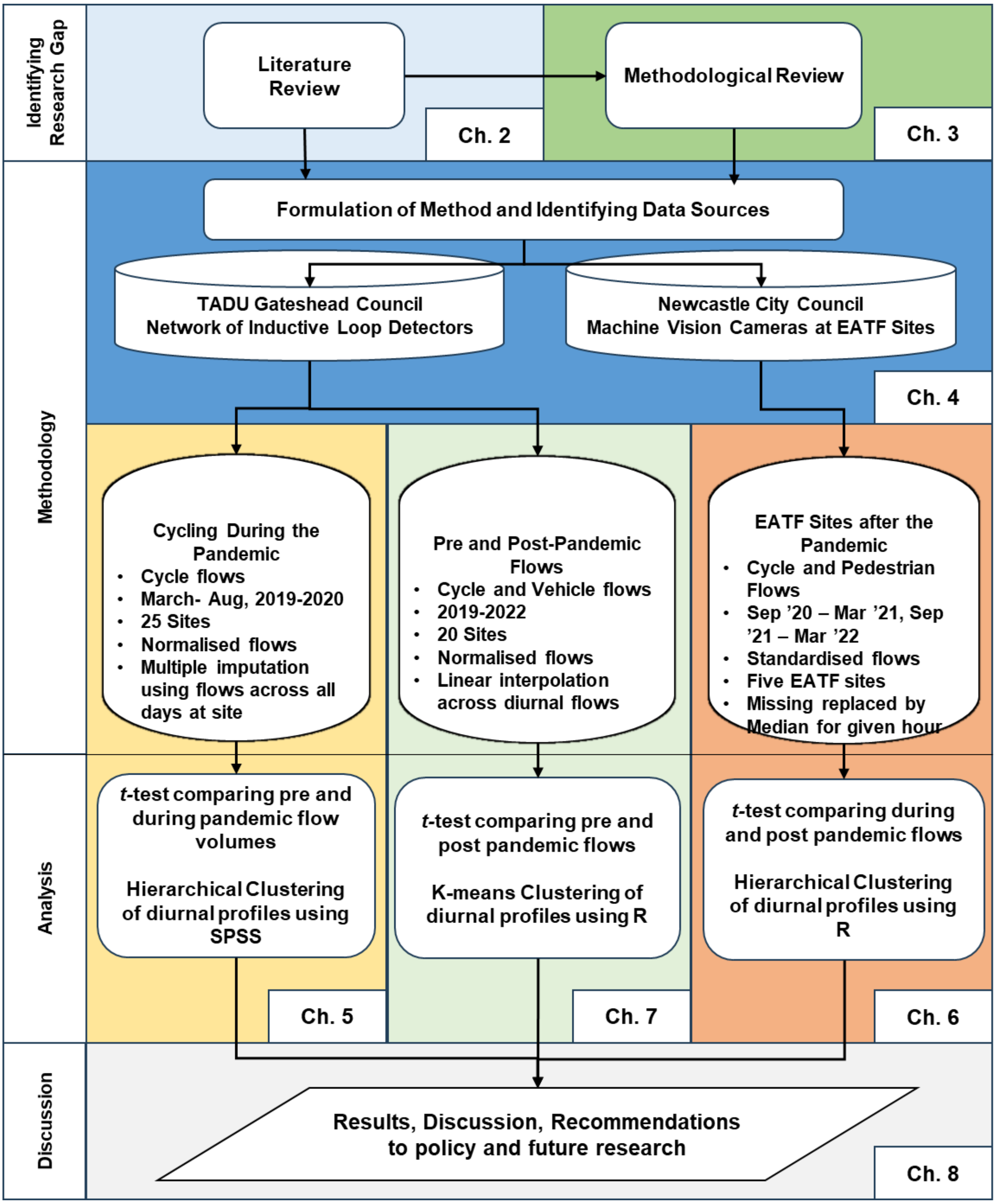

Figure 4.1 Methodological Flow Diagram

Figure 4.1 illustrates the order of research tasks that complete the thesis. The first task was to conduct a literature review of the emerging research studying the effect of the COVID-19 pandemic on flows of vehicle traffic and active travel, as well as the relevant government policy to identify the knowledge gap (Chapter 2). Secondly, a package of statistical tools and a methodological framework was developed through a critical review of the methods adopted by previous studies that analyse diurnal flow profiles with data clustering (Chapter 3). It is imperative to identify datasets that can ensure the research aim and objectives can be met, namely with historic data that spans before, during and after the pandemic, identifying limitations where appropriate (Chapter 4). Once these tasks are completed, the effect the pandemic had on cycling diurnal flows during the lockdown (Chapter 5) and its lasting effect in the post-pandemic period (Chapter 7). This will be with consideration of geospatial factors and infrastructure interventions (Chapter 6), as well as comparison with other modes of transport (pedestrians in Chapter 6, vehicles in Chapter 7). Finally, the last task is to discuss the results and suitability of the methodology and draw conclusions. Recommendations should be made to transport practitioners and for future research based on the findings of this study (Chapter 8).

4.2 Case Study – Tyne and Wear

It is important that the case study results in meaningful findings that have value from a global perspective. Therefore, this section demonstrates the suitability of Tyne and Wear as a case study. Firstly, Tyne and Wear faces transport issues common across the world that were identified in the literature review and, like many other places, aspires to move towards more sustainable travel. Moreover, it was severely affected by the COVID-19 pandemic.

Tyne and Wear is a metropolitan county situated in the North East region of England and has a population of approximately 1.13m people at the time of the 2021 Census (ONS, 2023). The population is spread across five local authorities; Gateshead (196k), Newcastle upon Tyne (300k), North Tyneside (209k), South Tyneside (148k) and Sunderland (274k). Overall, it is mixture of urban, suburban, coastal and semi-rural environments, with the two cities being Newcastle on the north bank of the River Tyne and Sunderland on the River Wear. Gateshead is primarily a large town sitting opposite Newcastle on the southern bank of the River Tyne, with small, semi-rural towns and villages also within the borough. The North Sea borders the east of Tyne and Wear, with towns along the coast such as Whitley Bay and North Shields within North Tyneside and South Shields within South Tyneside. Tyne and Wear is bordered by Northumberland to the north and north-west and County Durham to the south and south-west.

Tyne and Wear sits within the North East Joint Transport Committee (NEJTC), which brings together the five local authorities within Tyne and Wear with Northumberland and County Durham. This wider region has benefitted from allocations from the Transforming Cities Fund (TCF) and Active Travel Fund (ATF). For reference, the boundaries of Tyne and Wear and the NEJTC are shown in Figure 4.2.

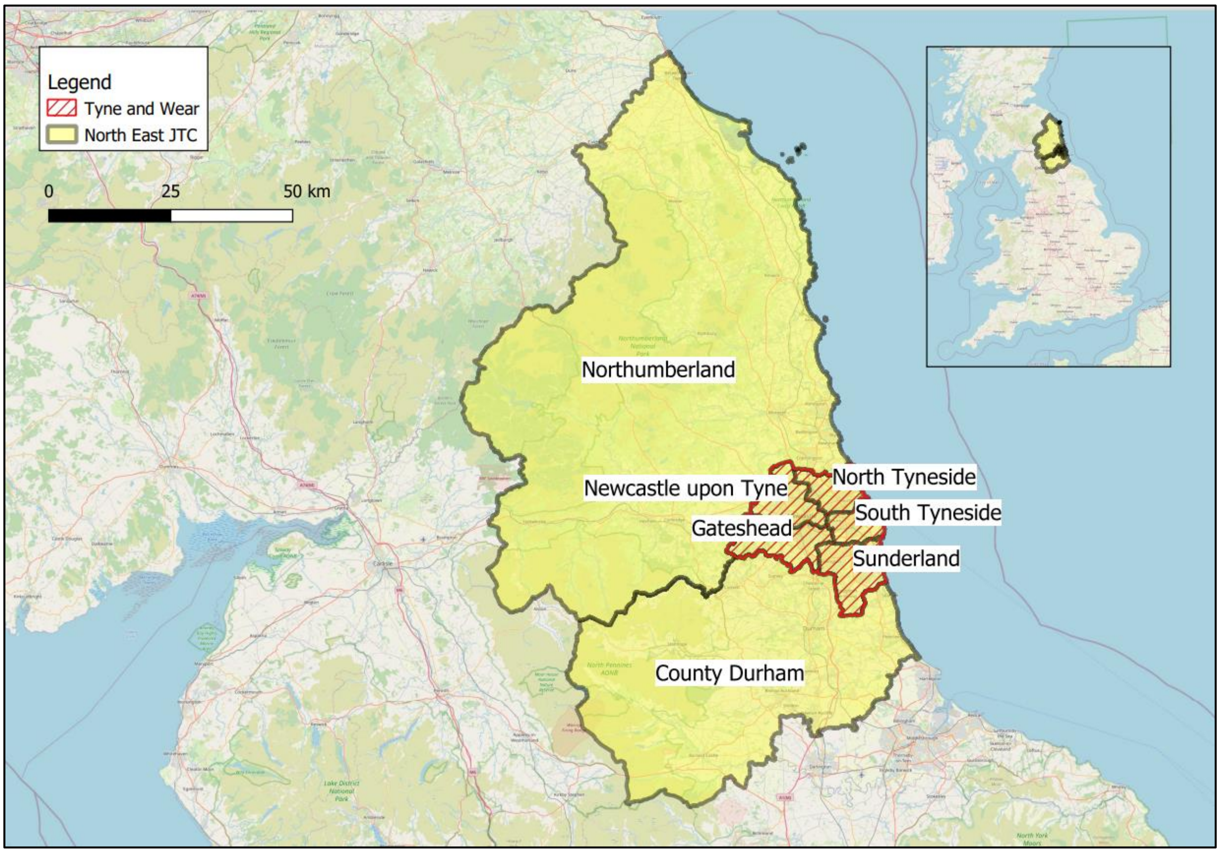

Figure 4.2. NEJTC and Tyne and Wear Boundaries within Great Britain

Major road links in Tyne and Wear include the A1(M) that runs through Gateshead and bypasses Newcastle to the west, offering a major north-south route. The A19 runs through North and South Tyneside, connecting the two regions by the Tyne Tunnel, whilst the A167 connects Newcastle city centre with the rest of the region via the Tyne Bridge. Other notable road traffic bridges include the Redheugh Bridge west of the Tyne Bridge and the Wearmouth Bridge in Sunderland. The A184 links Newcastle and Gateshead to Sunderland. Despite the abundance of strategic routes in the region, the North East suffers from significant congestion problems described in Section 4.2.1.

From an active travel perspective, there are a limited number of dedicated cycle paths in the region, including long-distance cycling routes such as Hadrian's Cycleway and the C2C (Sea to Sea) Route. As discussed in Section 4.2.1, most local cycle trips will involve a mix of segregated and on-road cycling, which, as stated in the literature review chapter, will have a negative impact on cycling uptake. There is also an extensive network of footpaths and pedestrianised areas, particularly in the city centres of Newcastle and Sunderland and along the quayside. Shared micro-mobility options are described in Section 4.2.1

The weather should be considered in line with active travel. The UK has a temperate climate, experiencing cool winters and warm summers. The North East is cooler and drier than other parts of the country (Met Office, 2024 https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/weather/learn-about/weather/regional-climates/north-east-england_-climate-met-office.pdf), however it is considered this should not be a limiting factor to adopting active travel, as the North East Transport Plan states that minimum temperatures are no lower than Amsterdam and Copenhagen, cities known for high levels of cycling, see Figure 4.3.

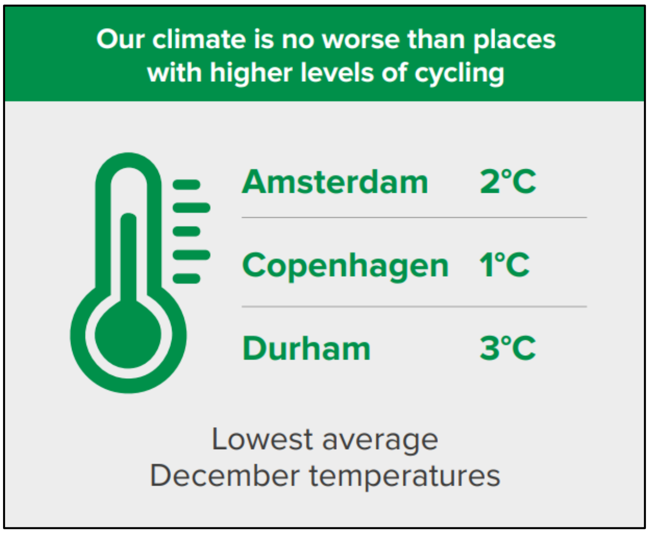

Figure 4.3. Comparison of Average Low Temperature in Durham, NE England and Cities with Cycling Cultures (NEJTC, 2021)

Additionally, Tyne and Wear has a variety of public transportation options, offering an alternative to the modes in focus in this thesis – namely driving, walking or cycling. The Tyne and Wear Metro is a light rail system that opened in 1980 and connects the boroughs of Tyne and Wear - Newcastle, Gateshead, South Tyneside, North Tyneside, and Sunderland, as well as connecting to Newcastle International Airport. In terms of bus services, several companies such as Go North East, Stagecoach, and Arriva operate networks that cover most areas within Tyne and Wear. Rail transport is well-represented with national rail services at Newcastle Central Station linking the region to major cities such as London, Edinburgh, Birmingham and Manchester. Newcastle International Airport, situated about six miles northwest of Newcastle city centre, offers both domestic and international flights.

4.2.1 Transport issues within Tyne and Wear

Despite having the highest proportion (28%) of households not owning a car in the UK outside of London (18%) (DfT, 2023a), the North East has significant road congestion problems. Moreover, road transport contributes to 37% of the total carbon emissions within the region, which is more than any other sector (NEJTC, 2021). Cars are the dominant mode for commuting in Tyne and Wear, accounting for 70% of the journeys. Conversely, cycling accounts for only 3.5% of total trips. These figures are comparable with the rest of England, which stands at 67% and 3.5%, respectively (DfT, 2023a). As with the rest of the UK, the ownership and use of cars in the North East is growing exacerbating the problems with congestion and hindering progress towards Net Zero (NEJTC, 2021).

In response, the North East region has made the improvement of Active Travel facilities a key policy area within the Local Transport Plan (2021-2035), with greater segregation of cyclists from motorised traffic cited as an important intervention (NEJTC, 2021). Whilst there have been some high-profile active travel infrastructure projects within the region, such as the reallocation of city centre road space from motorised traffic to cyclists on John Dobson Street in Newcastle City Centre, a typical trip by bicycle in Tyne and Wear requires some on-road cycling alongside motorised traffic. In the past, bike share schemes have been introduced in the region on two occasions, with ScratchBikes operating in Newcastle and Sunderland (2011-2013), and Mobike in Newcastle and Gateshead (2017-2019). Whilst a bike share scheme has not operated since then, the Neuron e-scooter share scheme has been operating since the beginning of 2021 in Newcastle and Sunderland.

4.2.2 Allocation of Funds for Active Travel to Tyne and Wear and the North East

Recognising issues and solutions within the transport network is only the beginning of the process. Having identified the importance of Active Travel in meeting the aims and objectives of the North East Transport Plan and wider national policy, Tyne and Wear and the wider North East region has received funding to promote such modes and to reduce congestion. Part of the £210m in funding the North East received as from the Transforming Cities Fund was spent on transport improvements; including public transport and improvement of the cycle network.

Additionally, as part of the Active Travel Fund, the NEJTC was allocated funds to promote active travel. NEJTC was awarded £2.3m in Tranche 1 of the funding, announced on 23rd May 2020 to support the installation of temporary projects during the COVID-19 pandemic, which included the EATF. Two further funds were announced on 14th May 2022 to support the creation of longer-term projects in the post-pandemic era. NEJTC was awarded £9m and £18m in these funds, respectively (DfT, 2020a).

The funding allocation demonstrates that increasing levels of active travel remains important whilst moving on from the pandemic. The North East receiving a significant proportion of the total national allocation of funds further demonstrates the suitability of Tyne and Wear as a case study given its commitment to improving active travel facilities.

Research into the use of active travel, both at EATF sites and across the wider transport network, as society settles into a 'new-normal' can create scientific evidence to enable decision-makers to invest awarded funds wisely. In the post-pandemic era knowing where and when during the day trips are made and inferring their purpose where possible, will be valuable when considering how best to spend the funds. The findings from the literature review (Chapter 2) suggested that when poorly implemented there was a mixed reception of such schemes before (Aldred et al., 2019) and during the pandemic (Nikitas et al., 2021).

4.2.3 Tyne and Wear and COVID-19

Countries across the world experienced different infection rates and their respective governments took different approaches to managing the pandemic by imposing lockdowns and restrictions differently. Even within countries, such as the UK, local lockdowns occurred differently, therefore it is essential to consider the specific conditions within Tyne and Wear and not just nationally.

With 388 deaths per 100,000 population, the North East was the second-most severely affected Regions within England, only behind the North West (393). England itself was one of the worst affected countries in the world, making Tyne and Wear a suitable case study considering the most severe impact of COVID-19 (UK Health Security Agency, 2023).

The UK entered its first national lockdown on the 26th of March 2020, restrictions were lifted incrementally until society was largely open once more on the 14th of August. However, amid increasing infection rates, local lockdown restrictions were enforced on the North East from the 18th of September 2020, including banning people socialising inside private homes with others outside of their household and curfews on pubs. Also, it was advised to avoid public transport, socialising in public spaces and attending sporting events. Only a few days afterwards on the 22nd, working from home restrictions were applied to England. By the 14th of October, the North East was placed under 'tier 3' local lockdown, the very high level of alert similar in restriction level to full lockdown. By the 5th of November, a national lockdown was announced, which remained in place until 7th of March 2021. A timeline of the three studies in the context of the COVID-19 pandemic lockdowns in the North East is provided in Figure 4.4.

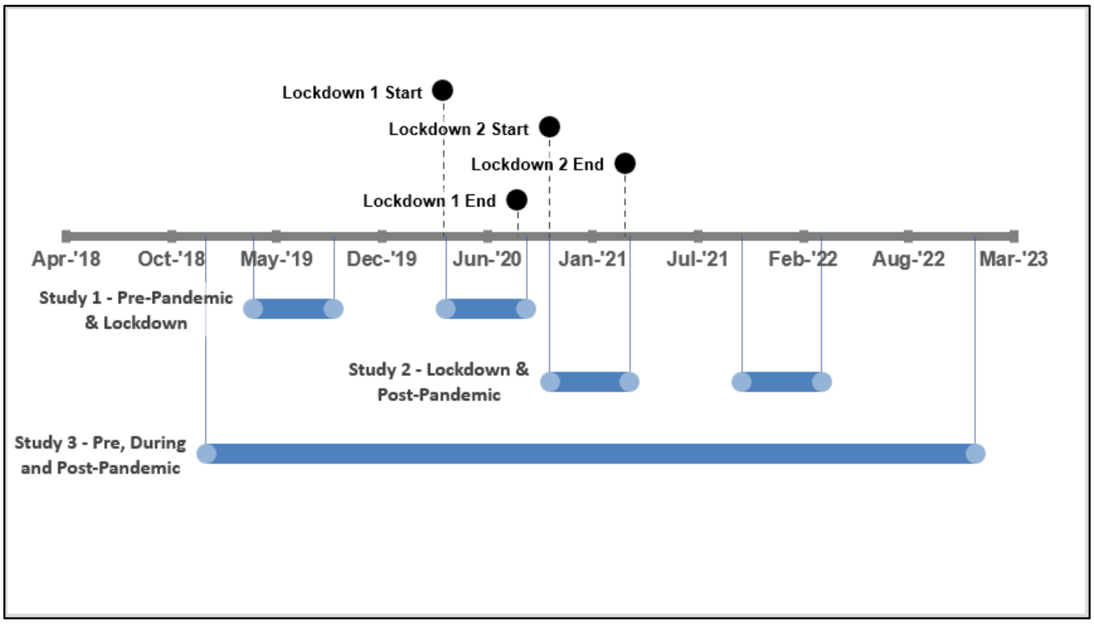

Figure 4.4. Three Study Periods in Relation to COVID-19 Lockdown

4.2.4 Summary of the Suitability of the Case Study

Like many places across the world, during times of lockdown it was found that with reduced car use, the COVID-19 pandemic lockdowns gave the North East region "cleaner and quieter towns, cities and neighbourhoods" (NEJTC, 2021). Due to the reduced levels in motorised traffic, this window in time offered local authorities a glimpse into how urban transport could look if future interventions were to replicate these conditions on a permanent basis, such as through the creation of segregated cycle routes and Low Traffic Neighbourhoods. Understanding the impact of these is of particular importance to future cycling investment, as the literature review has revealed safety fears are a major barrier to the uptake of cycling and lack of segregation from motorised vehicles is the main concern. Moreover, decision-makers will be keen to monitor the long-term trends in commuting that has been brought about by working from home practices accelerated by the pandemic and whether the long-assumed typical diurnal flow profiles remain representative of the post-pandemic era.

4.3 Obtaining Data from Third Party Sources

The literature review identified that whilst the studies into the early stages of the pandemic were insightful, there were limitations associated with the representativeness and size of the population sample in the study (Adibfar et al., 2022; Echaniz et al., 2021). Also, this was found on occasions in the review of pre-pandemic cycling literature (Broach et al., 2012; Mertens and Van Dyck, 2016). A quantitative data source that captures flows indiscriminately removes this limitation. The review of methods in Chapter 3 focused on quantitative data sets, specifically those where cluster analysis had been employed, demonstrating that a wide range of traffic flow data sets can be clustered so long as they follow a time series format. This encouraged the exploration of a range of different data sources before deciding upon conventional automatic traffic counters and the more novel data source in Machine Vision Cameras. Sections 4.3.1 – 4.3.3 will describe the process followed in this research to acquire the data.

4.3.1 TADU Data (Study 1 and 3)

In Tyne and Wear, the Traffic Accident and Data Unit (TADU) operated by Gateshead Council captures and stores transport data across the region. It is responsible for the maintenance, collection and provision of data over a network of approximately 450 automatic traffic counters (ATC) and 200 pedal cycle counters spread across the five local authorities that make up Tyne and Wear. Operational since 1986, TADU presents a valuable historical resource of longitudinal data. This wealth of information is available to the local authorities of Tyne and Wear as well as academic institutions through the TRAffic information DatabaSe (TRADS). This allows the transport community to plan, implement and research appropriate transport schemes across the county.

The Senior Transport Planner and Data Analyst at TADU was contacted in July 2020 who set up an account enabling access to the TRADS database. In preparation for the first study (results presented in Chapter 5) a search of the database identified 25 cycle sites across Tyne and Wear that had data uploaded to the TRADS database. Worthy of note is that many of the ATCs do not have remote download capability and require in person visits to the site to extract the data, which had not been achieved due to lockdown restrictions. Nevertheless, the 25 ATCs provided a good spread of sites across Tyne and Wear, and the availability of historical data was invaluable.

The availability of historic data across the entire study area meant TRADS was revisited in February 2023 to capture data for the third study, the results of which are covered in Chapter 7. Study 3 required traffic as well as cycle flows, therefore sites were identified where both were recorded as close as possible to one another, ideally at the exact same position. Moreover, the sites had to be functional before, during and after the pandemic. 30 potential sites were identified across Tyne and Wear that met the criteria. Under further inspection in the data preparation stage, this decreased to 20 sites. Due to the size of the dataset requested, it was necessary for the Senior Transport Planner to batch-download both the cycle and vehicle flows that covered all of 2019 through to the end of 2022, ensuring as much as the post-pandemic period could be studied within the final study.

4.3.2 Cycling and Walking Data at EATF Sites (Study 2)

An emerging topic of interest during the pandemic was the installation of pop-up active travel infrastructure funded by the EATF. In Study 1 it was found that one of the largest increases in cycling across the dataset was at a site that had EATF-funded interventions, Beverley Terrace in North Tyneside as part of the ‘Sunrise Cycleway’. Despite being an invaluable source of data, a limitation with TRADS is that the ATCs are at fixed positions and therefore TADU cannot react quickly to obtain counts at specific sites of interest, such as pop-up active travel infrastructure using the ATC network. This prompted exploration of alternative data sources to investigate additional sites that had seen pop-up infrastructure introduced using the EATF.

Inspired by Hong et al. (2020), the use of Strava Metro data was considered. The Strava Metro platform is a tool built to aid professional urban planners in planning bicycle and pedestrian infrastructure improvements and uses data obtained from the Strava social media app, which allows users to plot their bike rides and journeys on foot. A major advantage of Strava data is that there is data for every link of the transport network from main roads to off-road cycle tracks. Moreover, there is sufficient historical data to be representative of the pre-pandemic era. There are disadvantages though. One potential limitation with this data is that although Strava insist that it is representative of the general population, the only trips recorded are those using the mobile app, sampling bias associated with this are well-documented.

An application was submitted for access to Strava Metro in November 2020 however, due to the high volume of requests as a result of the rapid increase in cycling globally due to the pandemic, Strava was only able to provide access to groups directly and actively involved in transportation infrastructure planning. Whilst an alternative data source was found for Study 2, in April 2022 another application was made to Strava, this time successful. Upon exploring the datasets produced it was found that hourly flows were recorded in increments of five. As the purpose of the EATF schemes were to close smaller, quieter roads to through-traffic, cycle flows were already low, and the fact that only Strava users were counted meant that most hourly flows were categorised as ‘0’, ‘5’ or ‘10’ cycles per hour, creating limited variation in the diurnal flow profiles. This would not be an issue for busier routes and larger cities with more cyclists but would be a limiting factor for this particular study.

As mentioned previously, an alternative data source was found after contacting a Senior Transport Planner with Newcastle City Council (NCC) in October 2021 and enquiring about data availability for the EATF schemes. At the time, five schemes within Newcastle upon Tyne had already been through public consultation and were in the process of being made permanent. After a few meetings and allowing sufficient time until the schemes had been made permanent, data was received in May 2022. It was important to wait until the schemes had been made permanent as prior to this date, the data was politically sensitive. EATF and LTN schemes nationally have become controversial and are often met with strong opposition from sections of society. This was the experience for the sites within this study (Chapter 6), culminating in the online public consultation that ran alongside the trials being “hijacked”, leading to over 7,000 fake comments and 175,000 ‘agreements’ or comments being placed (Bradley, 2021).

Because no ATCs were located on the bridges within the schemes, Machine Vision cameras were installed that are able to automatically detect multi-modal flows, offering the opportunity to study pedestrian flows alongside cycling. The image in Figure 4.5 demonstrates how Machine Vision Cameras are able to both count and track multi-modal flows and is taken from Streets Systems website, the contractor collecting the data on behalf of NCC.

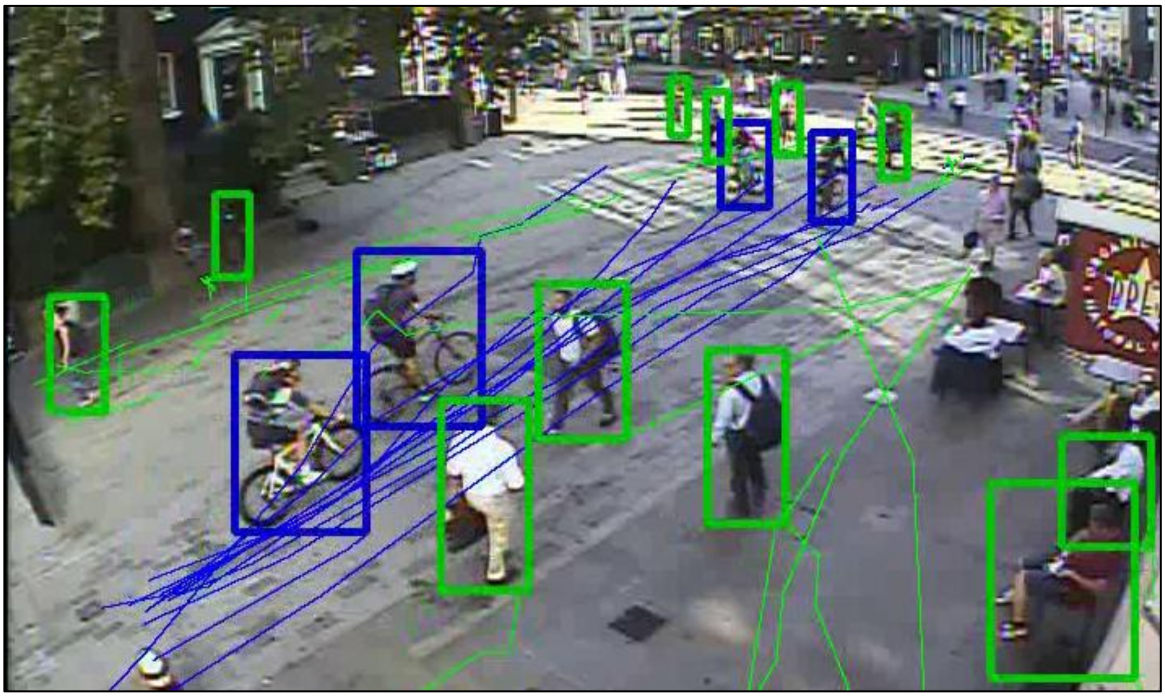

Figure 4.5. Multi-modal flows captured by Machine Vision cameras (Streets Systems, 2023)

4.3.3 Suitability of Technology Providing Traffic Flow Data

Both inductive loop detectors and video surveillance, or “Machine Vision Cameras” (MVC) are used within the studies of this thesis. Of the two, the inductive loop detector is the more mature technology, and most consistently accurate in terms of vehicle counts with a detection accuracy in the order of 95% (Briedis, 2010). Primarily used for traffic counts but they can also count cyclists, they consist of a loop of wire below the surface of the road and detects a change in the magnetic field when a metal object, i.e. a vehicle, passes over and sends a signal to a detector unit. As they do not rely on vision, loop detectors are not hindered by adverse weather conditions such as rain, snow or fog or low-light conditions during night time. The main disadvantage of inductive loop detectors is that they require burying under road surfaces, meaning they are disruptive when installing and immobile. Moreover, one loop can only detect one lane of traffic or record more than one vehicle at a time (Fiore et al, 2019).

MVC counters automatically analyse video images using deep learning algorithms, which can detect and classify multi-modal flows. Whilst the technology and operational cost of MVC may be higher than inductive loop detectors, they are far less disruptive to the road network to install. Another benefit is they can detect multi-modal movements including pedestrians and cyclists, and one counter can detect many subjects at once. In crowded locations this can impact detection accuracy, with one study reporting as low as 61% detection rate. (Guha, 2006), however over 95% accuracy was found in more straight-forward highway conditions (Kanhere, 2008). One disadvantage of MVC is that they can be sensitive to bad weather (Buch et al, 2011). Poor lighting or nighttime conditions can reduce their accuracy unless complemented with proper lighting or infrared capabilities. They require regular cleaning and maintenance to ensure lenses are not obstructed by dirt, dust, or debris (Fiore et al, 2019).

Whilst comparing the accuracy of the technologies is beyond the scope of this research, it is not expected that any of the sites where MVC is deployed will be busy enough to go beyond the limitations of the technology and both are deemed appropriate for the research in this thesis.

4.3.4 Data Source Summary

A summary of the data sets acquired for the three studies is presented in Table 5.

Table 5. Summary of Data Sets Used

Study	Topic	Time Period	Modes	Source	Number of Sites
1	Cycling during the Pandemic	Mar 1 – Aug 31 Pre-Pandemic (2019) and during Pandemic (2020)	Cycling	TADU	25
2	EATF sites after the Pandemic	During 2nd Lockdown (Oct 2020 – Mar 2021) and Post-Pandemic (Oct 2021 – Mar 2022)	Cycling and Pedestrians	NCC	5
3	Traffic and Cycling flows Before and after the Pandemic	Pre through to Post-Pandemic (2019 – 2022)	Cycling and Traffic	TADU	20

4.4 Data Preparation

The methodological review Chapter 3 identified that observational-based clustering was a suitable approach when investigating the geometric shape of time series data. The raw data requires some pre-processing steps. This section will demonstrate the stages involved with preparing the data for clustering.

4.4.1 Formatting Data

Figure 4.6 shows the structure of the Excel files received from TADU. Each row represents a specific day, mode and direction whilst each column is a count for each hour in the day.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
1	SiteNo	Date	Hour1	Hour2	Hour3	Hour4	Hour5	Hour6	Hour7	Hour8	Hour9	Hour10	Hour11	Hour12	Hour13	Hour14	Hour15	Hour16	Hour17	Hour18	Hour19	Hour20	Hour21	Hour22	Hour23	Hour24
2	201	01/01/2017	374	351	380	360	269	154	190	202	134	177	251	414	516	540	510	482	459	413	409	380	305	268	287	254
3	201	02/01/2017	194	128	90	108	67	120	191	313	348	424	603	809	865	894	813	657	619	561	526	475	407	318	284	237
4	201	03/01/2017	162	87	70	48	85	170	700	2023	1624	1066	893	938	906	1229	920	829	885	942	622	517	392	287	244	200
5	201	04/01/2017	116	70	64	43	69	168	752	2012	1620	1175	983	945	897	1006	884	828	921	971	713	574	380	283	242	227
6	201	05/01/2017	115	72	44	38	62	156	713	1821	1568	1274	1016	969	981	939	907	876	895	1030	753	540	408	316	235	248
7	201	06/01/2017	119	89	49	58	66	156	739	1981	1772	1232	1020	934	1045	1057	937	908	930	982	834	693	447	360	299	280
8	201	07/01/2017	249	167	133	109	81	121	271	476	659	772	906	990	1050	1088	1025	886	769	790	747	631	477	407	380	407
9	201	08/01/2017	299	241	203	204	102	104	185	253	279	424	747	869	901	917	746	696	677	654	567	447	338	248	233	266
10	201	09/01/2017	156	87	67	57	82	190	836	2030	1363	1007	986	954	891	970	917	849	946	1012	827	598	391	311	263	204
11	201	10/01/2017	160	78	51	51	74	186	859	2103	1426	1283	1053	967	971	944	874	921	985	1126	899	575	442	291	254	199
12	201	11/01/2017	116	74	41	59	54	181	816	1993	1061	1153	1053	926	945	958	813	935	976	1050	858	575	391	296	250	241
13	201	12/01/2017	112	77	41	53	70	166	825	1904	1535	1044	1044	1000	1039	1003	996	1048	1134	1386	1097	694	464	363	378	315
14	201	13/01/2017	181	92	66	73	80	142	660	1766	1362	1274	1041	914	1016	1038	936	1003	976	899	786	670	466	393	314	336
15	201	14/01/2017	251	174	139	153	102	132	287	483	667	826	981	1013	1127	1166	1051	897	848	785	806	740	469	408	404	424
16	201	15/01/2017	366	292	245	249	140	120	198	265	288	358	757	882	926	908	772	738	675	637	551	451	362	286	219	256
17	201	16/01/2017	151	90	50	53	73	191	812	1888	1043	1019	1137	1032	1031	1087	905	888	1020	1113	868	599	400	301	265	233
18	201	17/01/2017	139	79	56	54	73	185	886	1580	1457	988	1107	944	956	938	849	853	998	990	895	651	410	334	255	202
19	201	18/01/2017	131	75	46	59	70	177	869	1808	1268	1039	1107	992	1003	989	858	933	1073	1050	635	665	435	477	325	269
20	201	19/01/2017	156	87	63	57	66	185	818	2041	1324	1249	1135	1031	980	926	913	908	989	1043	1001	733	529	375	294	272

Figure 4.6. Screenshot of Raw TADU data (Study 1 and 3)

Referring to Figure 4.6, the left-most column of the table begins with the site number, with the two last digits signifying the direction of the traffic. In the example, the diurnal flow profile is for Site 2, and "01" indicates the direction of travel, in this case the northbound flow on the Redheugh Bridge that carries traffic over the River Tyne in Newcastle. The VLOOKUP function was then used in conjunction with an information table provided by TADU to link the site name and local authority for each diurnal flow. On the few occasions where there was no record of the site name and number within the lookup table, the correct site name was manually located on TADU's Automatic Traffic Counter Dashboard (TADU, 2023)

The column to the right of the site number indicates the date, which prior to analysis are converted to ISO time format of YYYY-MM-DD. New columns were then created for the day of the week, the month and year using the TEXT function and referring to the ISO date. The hourly aggregated traffic flows then make up the following 24 columns of data.

The NCC data required a few additional steps to transform the data into a diurnal time series in the same format as the TADU data. Figure 4.7 shows the raw format of the flow data.

	A	B	C	D	E	F
1	dt	value	veh_class	dir	location	category
92	09/02/2022 08:30	2	pc	from_east_to_west	NclStoneyhurstRectory	flow
93	09/02/2022 08:30	9	person	from_east_to_west	NclStoneyhurstRectory	flow
94	09/02/2022 08:30	1	pc	from_west_to_east	NclStoneyhurstRectory	flow
95	09/02/2022 08:30	9	person	from_west_to_east	NclStoneyhurstRectory	flow
96	09/02/2022 08:45	6	pc	from_east_to_west	NclStoneyhurstRectory	flow
97	09/02/2022 08:45	13	person	from_east_to_west	NclStoneyhurstRectory	flow
98	09/02/2022 08:45	5	pc	from_west_to_east	NclStoneyhurstRectory	flow
99	09/02/2022 08:45	94	person	from_west_to_east	NclStoneyhurstRectory	flow
100	09/02/2022 08:45	1	buggy	from_east_to_west	NclStoneyhurstRectory	flow
101	09/02/2022 09:00	3	pc	from_east_to_west	NclStoneyhurstRectory	flow
102	09/02/2022 09:00	25	person	from_east_to_west	NclStoneyhurstRectory	flow
103	09/02/2022 09:00	1	pc	from_west_to_east	NclStoneyhurstRectory	flow
104	09/02/2022 09:00	10	person	from_west_to_east	NclStoneyhurstRectory	flow
105	09/02/2022 09:15	5	pc	from_east_to_west	NclStoneyhurstRectory	flow
106	09/02/2022 09:15	6	person	from_east_to_west	NclStoneyhurstRectory	flow
107	09/02/2022 09:15	4	person	from_west_to_east	NclStoneyhurstRectory	flow
108	09/02/2022 09:15	1	pc	from_west_to_east	NclStoneyhurstRectory	flow

Figure 4.7. NCC Raw Data for Study 2

The vehicle class column shows that as well as pedestrian (person) and cyclists (pc), machine vision cameras are able to capture prams being pushed (buggy) and wheelchair users. Analysing the latter two would provide valuable insight into the mobility of under-represented groups, however it was apparent at this early stage in the data preparation stage that in this dataset there were insufficient flows of these modes to produce meaningful results. Cameras capturing busier parts of the city would provide a valuable resource for further study in this area.

The date and hour of day were separated into two columns from the leftmost column named 'dt'. Using Excel, a Pivot Table was created that enabled in one step the segregation of modes, merging of directions, aggregation of flows to an hourly time period, and restructuring of the data so that individual diurnal flows were represented by rows and hourly counts by columns similar to the TADU data in Figure 4.6.

4.4.2 Identifying and Replacing Missing data

Missing data will result in the generation of false diurnal flow profiles and is likely to prevent the analysis software from successfully performing the clustering. Therefore, it was necessary to remove any diurnal flows that were too incomplete for imputation, the criteria for which will be discussed later in this section.

A column was created using the COUNTIF function to sum up the blank hourly flow counts within each unidirectional diurnal flow. Once the directions were merged, these counts remained visible. Deleting the missing flows before pairing with its opposite direction would disguise the fact that one direction was missing data if the other was recording. It was found in most instances, if data was missing in one direction, it was missing in the other. Given the importance of a complete dataset, availability of substitutes and reliability of recording differed across the three studies, different approaches were taken with the handling of missing data. A summary of the data cleaning process for each study is provided below.

An upper limit to the number of hourly missing count data needs to be decided and diurnal flow profiles above the threshold deleted prior to the aggregation. The study by (Shafique, 2022) suggested that diurnal flow profiles that have more than five missing hourly flows should be excluded.

In Study 1, there was a need to include as many sites that had recorded data in 2020 as possible. If a site with valid diurnal profiles in 2020 data had not been recorded in 2019, 2018 data was substituted to maximise available sites. This was on the basis that DfT statistics (DfT, 2021c) revealed that there was a 0.5% decrease in total distance cycled between 2018 and 2019 in North East England, therefore, in the context of the unprecedented change witnessed during the pandemic, it is considered acceptable and appropriate to substitute 2018 for 2019 data. Where there were five or less missing hours, multiple imputation was carried out in SPSS.

With Study 2, the data came from Machine Vision Cameras, MVC, rather than inductive loop detectors. On inspection of the data, there were few missing hourly counts. However, there was a need to estimate night and early morning counts for the first few weeks of the survey period, as it was apparent the MVC had not been recording. The median was used for these hours, according to day of week, the site and whether it was during or post-pandemic period. This was chosen because the flows during the night and early hours of the morning were very low, often 0, therefore the median deemed most appropriate.

For Study 3, it was possible to use linear interpolation for diurnal flow profiles with at least one and up to five blank hourly counts to enable them to be included for the clustering. This was achieved using the statistical package R.

Linear interpolation (LI) was seen as an improvement over methods such as the mean or median for a given hour as it only takes into consideration the flow profile itself. With other methods, e.g., substitution by median as used in Study 2, a conscious decision would have to be taken as to which other flows would be considered appropriate to represent the missing data, including the day of week and time of year. LI does not consider any of these factors, as it estimates missing data between two known hourly counts by assuming a constant rate of change between them. This method is appealing for not just its simplicity but because the data is not pre-classified in any way beforehand. One of the main motivations of the study is to establish whether the standard 9-5, Mon-Fri working week still exists and imputing missing data based on the assumption that this is still the case defeats the point of the study. As mentioned previously, because the flows being replaced in Study 2 were during the night, the median was almost always 0 and the imputation method selected had a negligible effect on the results. Linear interpolation was carried out using the ‘na.approx’ function from the ‘zoo’ R package. The one-directional diurnal profiles can now be merged to create two-way diurnal flow profiles.

4.4.3 Normalising data

One of the findings from the methodological review was the importance of normalising the diurnal flows, particularly when clustering a dataset with several sites in one analysis. Two methods were subsequently identified. Within traffic studies, dividing by the mean as expressed in Section 3.5.5 was the most commonly adopted approach, therefore it will be adopted for the normalisation of the TADU data in Studies 1 and 3. For clustering in general, the z-standardisation method is often suggested and Section 3.5.5 stated that z-standardisation is better suited to datasets with more variability than normalising around the mean (Nicholson et al., 2022).

Unlike the other two studies, Study 2 was conducted solely in the autumn, winter and early spring months. Furthermore, the locations are mostly less-travelled than the strategic routes that are captured by TADU's network of inductive loop detectors, hence why they were identified as appropriate to close to vehicular traffic. With diurnal flows possessing lower counts, each individual pedestrian or cyclist represents a larger proportion of the total flows. This means that any change in a single unit has a more significant impact on the overall variability. Therefore, variability across the day and study period is expected to be higher and it was decided to use z-standardisation for Study 2.

4.5 Critical Discussion on Suitability of Data

Section 4.4 has explained the source and steps of preparation for the data prior to the analysis within this thesis. Both types of traffic counting technology faced challenges, the inductive loop counters suffered with a lack of a complete datasets at many of the 500 inductive loop detector ATC sites across Tyne and Wear, often due to the lack of remote download capability in time of a pandemic. MCV on the other hand struggle with adverse weather and low light conditions. Even after considering these issues, Section 4.4.2 outlines the requirement for imputation of further unexplained missing data in each of the three studies, each possessing a bespoke solution the problem.

Whilst these issues were overcome with the data preparation outlined in this section, they should be considered as a small limitation of this any study that relies on technology to count traffic. However, without these technologies studies such as the three presented in this thesis would not be possible. Technological advancements particularly with the newer MVC counters will reduce the effect on studies in the future. To conclude, it is considered the data collection and preparation is suitable for the research conducted for the purpose of this PhD.

4.6 Analysis

This section discusses the methods adopted for the analysis of the three studies. Each follow the same steps with a few adjustments specific to the requirements of the data and study objectives. The experience gained from one study informed the next one, and evidence of personal development can be seen through the uptake of the statistical package R to perform the cluster analysis from Study 2 onwards.

4.6.1 Determining change in flow volume over time periods

The first objective of the research reported in this thesis was to identify whether there has been a change in the volume of traffic in relation to the pandemic, whether before, during or after. Flow volumes according to site and week of the year were compared across the two time periods of each study (e.g. pre and post pandemic). Daily averages across the week were used to avoid comparing different days of the week, e.g. a weekday with a weekend day as suggested by (Liu & Stern, 2021).

4.6.2 Performing the cluster analysis

The methodological review covered in Chapter 3 revealed that Hierarchical and k-means are the most commonly used clustering algorithms. Those that use hierarchical state the benefit is the number of clusters does not need to be determined before performing the analysis. Of those that used hierarchical cluster analysis, most commonly chose Ward's method (see Section 3.6.1) to define distance between clusters (Weijermars & van Berkum, 2005; Thomas, 2008; Jimenez & Vega, 2021) because it produces similar-sized clusters and therefore was the chosen method for Study 1 and 2.

The clustering of the diurnal flow profiles was performed in statistical software packages. In Study 1, SPSS was used. Necula (2015) found R to be capable of clustering large time series datasets. Therefore, after attending the courses "Introduction to R", "Statistical Modelling with R" and "Programming with R" held by Newcastle University during November and December 2021 it was possible to perform Ward's method in R Studio for Study 2. The 'hcut' function was used in R to perform the hierarchical cluster analysis, with 'fviz' functions from the factoextra package used to visualise the results.

Developing the methodology further, an additional aim for Study 3 was to compare Ward's method with the other clustering method frequently adopted namely Partitional *k*-means clustering (see Section 3.6.2). Due to the computational processing demand of the dataset, 2019 vehicles flows were used as a sample and two indices (WSS and Silhouette) were used as evaluation statistics for the two methods across a range of cluster number solutions, described in the following Section (4.6.3). The R script for both clustering methods has been included in Appendix A of the thesis and will be made available to use for future studies as per the research objective 4: "*To explore the requirements to create an analysis tool based on the methods developed in this research for future studies"*.

4.6.3 Determining the Number of Cluster and Validation of Results

Various methods can be employed to identify the optimal number of clusters into which to split the diurnal flow profiles, as described in Section 3.6.5 of the methodological review chapter. For this thesis, a selection of methods has been used to inform the decision as to how many clusters to use in each of the three studies.

Firstly, the sum of squared deviations from the mean, or the within sum of squares (WSS), is an important measure in clustering. The previous chapter explained how Ward's Hierarchical method fuses clusters at each agglomeration stage based on minimising the total WSS across the dataset. The total WSS therefore can be used to measure the similarity within a specific cluster solution. Plotting the total WSS whilst incrementally increasing the number of clusters within the solution helps determine the optimal number of clusters, using the 'elbow' approach. The scree plot begins with plotting the first divide of the full dataset into a two-cluster solution, which provides the greatest reduction in the total WSS, with each increase in the number of clusters having a diminishing effect on the reduction in WSS. The optimal number of clusters is suggested to be at the point where there is a noticeable drop, or point of inflection, in the reduction of WSS for a subsequent increase in the number of clusters, thus the 'elbow' of the line. This method is applied in all three studies as it is not exclusive to either Ward's or k-means.

Unlike partitional clustering methods, hierarchical clustering provides results of the full structure of the data displayed as a dendrogram, see examples presented in Figures 6.16 and 6.22 in Chapter 6. For the analysis purposes of this research, like most others, the clustering results at only one level of the hierarchy is necessary. Another option to the elbow plot to determine the optimal level is to 'cut' the dendrogram at a point where further agglomeration, or fusion of clusters, brings together individuals that are deemed not representative of one another. For Study 1, the dendrogram was displayed with each cluster represented by the number of individuals within each at each stage of the agglomeration. For Study 2, the dendrogram was plotted using the 'fviz_dend' function in the factoextra package in R.

Turning the attention to k-means, the Silhouette Index, developed by Rousseeuw, (1987) produces a graphical display for partitional clustering techniques. It was seen as a way of presenting partitional clustering results in an aesthetic way, similar to the dendrogram within hierarchical clustering methods. Each cluster is represented by a silhouette that represents its tightness within the cluster and separation between clusters. Each diurnal flow profile is represented in the silhouette of its respective cluster, and each silhouette can be plotted to gain an appreciation of the overall quality of the clustering and structure of the data. The average silhouette width provides an evaluation of clustering validity and may be used to select the optimal number of clusters for the analysis (Rousseeuw, 1987).

Ultimately, the choice of number of clusters depends on the purpose of the study. As the aim of the research reported in this thesis is to identify general trends in the post-pandemic travel behaviour, the discussion is likely to benefit from a smaller number of clusters than compared to, for example, a study that would rely on the clusters to forecast future traffic flows precisely such as Soriguera (2012), which would require clusters with as low WSS as possible.

4.7 Summary of Methods Chapter

This chapter has presented the methodological framework of the three studies that will be used to meet the research objectives, namely a comparison of pre-, during and post-pandemic diurnal flow profiles using cluster analysis, performing this analysis across both vehicle and active travel counts. The research conducted for this thesis consists of three separate studies, with the nuances and results of each discussed in turn in the three chapters following this one.

Tyne and Wear, UK was chosen as a case study area which the data from all three of the studies are collected within. As well as facing similar transport issues as many parts of the world, Tyne and Wear was also seriously affected by the COVID-19 pandemic, being one of the worst hit regions of one of the worst hit countries globally.

Chapter 5 will contain the details from Study 1, the analysis of data from the cycle counter network operated by TADU. After the data is cleaned and processed the hourly flows are normalised. Hierarchical Cluster Analysis (HCA) is performed on the cycling diurnal flow profiles to compare their shapes before the pandemic and during each stage of the 2020 lockdown. HCA was selected as the number of clusters does not need to be determined before performing the analysis (Weijermars & van Berkum, 2005; Thomas, 2008; Jimenez & Vega, 2021).

Chapter 6 covers Study 2, which utilises pedestrian and cycle flows captured during and after the pandemic with Machine Vision Camera across five EATF sites by Newcastle City Council. Similar to Study 1, the data is cleaned and processed, however the hourly flows are standardised rather than normalised due to this method being more appropriate for handling higher data variability (Nicholson et al., 2022), of which it is expected this dataset will be.

Chapter 7 contains the last of the studies, 3. Data is once again collected from TADU. Counters whereby cycling and vehicle flows are collected were identified, and the study period was extended to four years (2019-2022) in order to understand the post-pandemic trends. The data was normalised; however k-means was adopted for Study 3, due to its lower computational demand (Karthikeyan et al. (2020) and Gupta et al. (2021). Study 3 was the largest dataset spanning four years of data and this was a required step to complete the analysis.

The findings of all three studies are then discussed in Chapter 8, commenting on the appropriateness of the methodology and its limitations. Then the results and their implications to policy. Future studies are then recommended before the thesis is concluded.

Chapter 5. COVID-19 Lockdown and Cycling Flows

5.1 Introduction

This chapter will present the specific details of data collected, analysis, results and discussion of the first of the three studies carried out in the research reported in this thesis. The study investigating cycling flow profiles during COVID-19 lockdown in the UK between March to August 2020 was carried out during the second half of 2020, a time of brief relief from COVID-19 and the associated lockdowns. This provided a short window of time to reflect on the drastic disruption to the transport sector.

The large, unexpected uptake in cycling was seen as a positive amongst the many negative aspects of the pandemic and an in-depth understanding of this change is important given the difficulties faced promoting active travel before the pandemic. Researchers were quick to present results from the early lockdown period but in hindsight it is known that society was eased out of lockdown over a much longer period of time. As revealed in the literature review, Chapter 2, questions were being asked about whether the boom in cycling would remain after lockdown, or whether it was only due to the unique set of circumstances associated with lockdown that was the cause.

This research aimed to contribute to the understanding of these questions by allowing sufficient time to elapse after the initial lockdown in the UK to observe how cycling flows would change as lockdown was gradually eased and the first few months of no restrictions by analysing the data up until the end of August 2020.

5.1.1 Data Collection and Preparation Stage

TADU automatic cycle counters were searched to identify sites with data recorded during the lockdown period. Data were available from 25 detectors across Tyne and Wear, and their locations are marked on Figure 5.1.

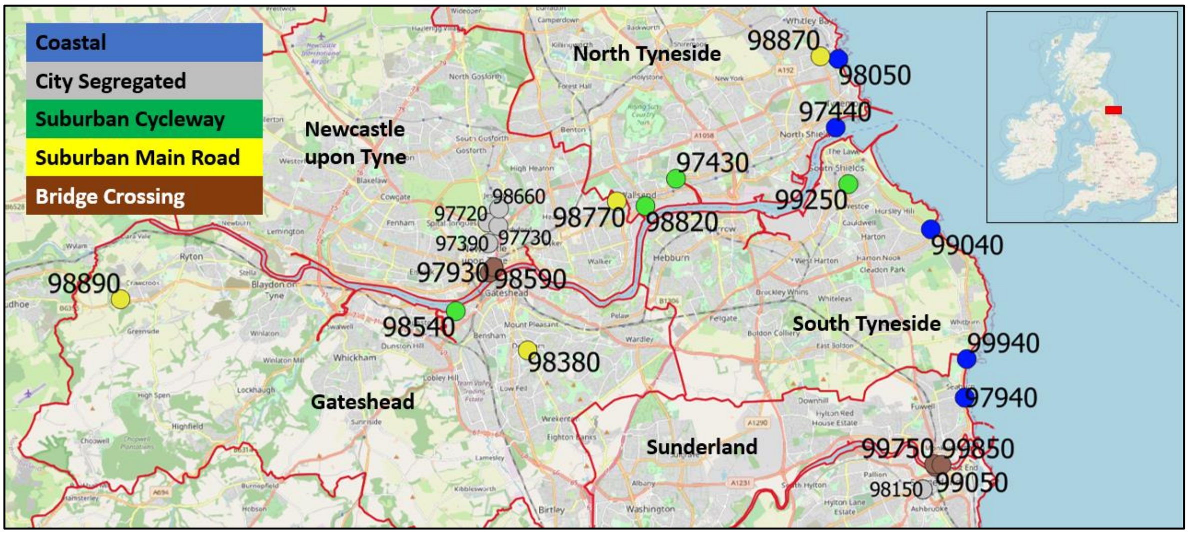

Figure 5.1. 25 Counter Sites for Study 1

The locations are spread across all five local authorities within Tyne and Wear and are colour-coded based on general location and, although not limited to the trip purposes described, anticipated trips are suggested in Table 6.

Table 6. Key for Location type of Cycle Counters

Colour		Counter Location Type	Description	Anticipated Trips
Blue		Coastal	Coastal counters are segregated from motorised traffic, and directly on the North Seafront.	Recreational
Grey		City	Segregated counters within or on the edge of the city centre.	Commute, Studying, Shopping
Brown		Bridge Crossing	Segregated counters on bridges or in their immediate vicinity, over the River Tyne or Wear.	Commute, Shopping, Recreational
Green		Suburban Cycleway	A segregated cycle path in a suburban area.	Commute, School Trips, Recreational, Grocery Shopping
Yellow		Suburban Main Road	Main road shared with motorised traffic in a suburban area.	Commute, Grocery Shopping

Cycle flow data captured from the database at the 25 sites were screened further for any missing data during 2019. Data missing in 2019 were substituted with 2018 and constituted 5.6% of the total. DfT statistics reveal that there was a 0.5% decrease in total distance cycled between 2018 and 2019 in North East England (DfT, 2021c), in the context of the change resulting from the pandemic, this small difference is considered acceptable justifying the substitution of 2018 for 2019 data. 2018/19 data will be referred to as the 'Pre-COVID' year in this section.

Extra consideration in the data preparation stage was needed for counter 98050, situated by the coast on Beverley Terrace, Cullercoats (see Fig. 5.1). This was the location of an EATF-funded, pop-up two-way cycleway on the southbound lane of the main traffic carriageway, known as the ‘Sunrise Cycleway’. As a result, cyclists who would have used the parallel, shared-use path were instructed to use the pop-up cycleway, leaving the shared-use path for the use of pedestrians only. There was an inductive loop detector already installed in the main carriageway, therefore it was possible to add the cycle flows from this counter to the shared-use flows to ensure all cyclists were accounted for after the Sunrise Cycleway was introduced.

Whilst it was possible to include this site from a data availability perspective, there are implications to using data from sites where EATF interventions have been introduced. However, these can be mitigated through appropriate methodology, and such data offer valuable insights into how new policies have affected cycling behaviour.

An EATF intervention is likely to influence the desirability of the route, leading to a different response compared to non-EATF sites where such interventions were not implemented. This could skew the analysis by attributing changes to COVID-19 effects rather than to the intervention. However, in the case of the Sunrise Cycleway, as Beverley Terrace already has a shared-use path parallel to the EATF intervention, cyclists were segregated from vehicle traffic before its introduction. If only on-road cycling had been available previously, it could be assumed that any effect would be greater as the literature review chapter showed that this segregation is important in encouraging new cyclists.

Methodologically, normalising flows across the day mitigates the effect of a large change in flow volume on the clustering of diurnal flow profiles. Cluster analysis aims to group similar flow profiles together. Therefore, if the flow profiles resulting from the EATF site are dramatically different from previous ones, this will be reflected, and these flows could form their own cluster, enriching the discussion of results.

Another factor to consider is that the dataset already contains a large amount of heterogeneity through the use of 25 cycle locations spread across Tyne and Wear, each with different characteristics. Additionally, diurnal flows generally differ between weekdays and weekends, and the dataset includes both pre-COVID and lockdown periods. The purpose of this study is to investigate differences, which relies less on homogeneity than forecasting does.

In addition to demonstrating that the methodology is well-suited to accommodating the presence of a pop-up cycle lane in the dataset, there are also reasons to justify its inclusion. Firstly, with £2.5 million spent on EATF interventions across the UK, the pandemic saw numerous emergency measures aimed at promoting cycling. Including EATF sites ensures that the analysis accurately represents the conditions and responses during the pandemic, offering a more realistic depiction of the situation. Secondly, including EATF sites allows for the assessment of how emergency measures influenced cycling diurnal flow profiles. This is crucial for future planning and can guide the design of similar interventions in response to crises.

5.1.2 Analytical methods used

The analysis was carried out in three stages. Firstly, the changes in the weekly flow levels generally across Tyne and Wear were explored. Next Hierarchical Cluster Analysis (HCA) using Ward's method was performed using Euclidean distance. The flows were normalised by dividing the observed hourly cycle flow by the mean based on 24 hours, as described in Section 3.5.5. Finally, by integrating the HCA outputs with the changes in flow volumes, any relationships between the change in flows and the prevalence of a particular shape of the diurnal cycling flow profile was determined. This is analysed with reference to geospatial and temporal factors, including an investigation of the impacts of the different levels of Government restrictions during the lockdown.

5.2 Change in Volume of Flows

Figure 5.2 shows the average change in weekly cycle flows from 1st March to 31st August from the Pre-COVID year to 2020 at the 25 detector sites. The distribution of points about the Y=X line demonstrates that cycle flows have increased at more locations (61%) than have decreased (26%) in 2020, whilst 13% of detectors remained relatively unchanged. Across all sites, there was a mean increase of 373 flows (±95% confidence interval, CI of 280 – 466).

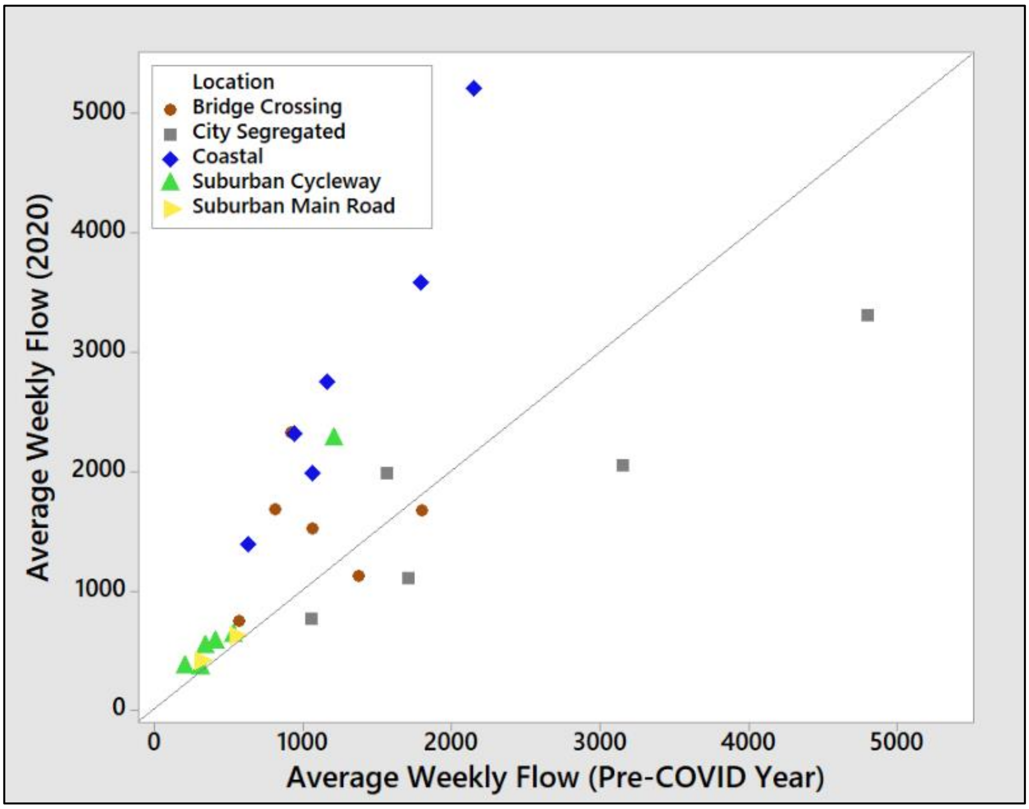

Figure 5.2. Change in average weekly flow pre / during COVID-19

A histogram was plotted of the difference between years, shown in Figure 5._ The data appears generally normally distributed, with steeper sides and a slight right skewness.

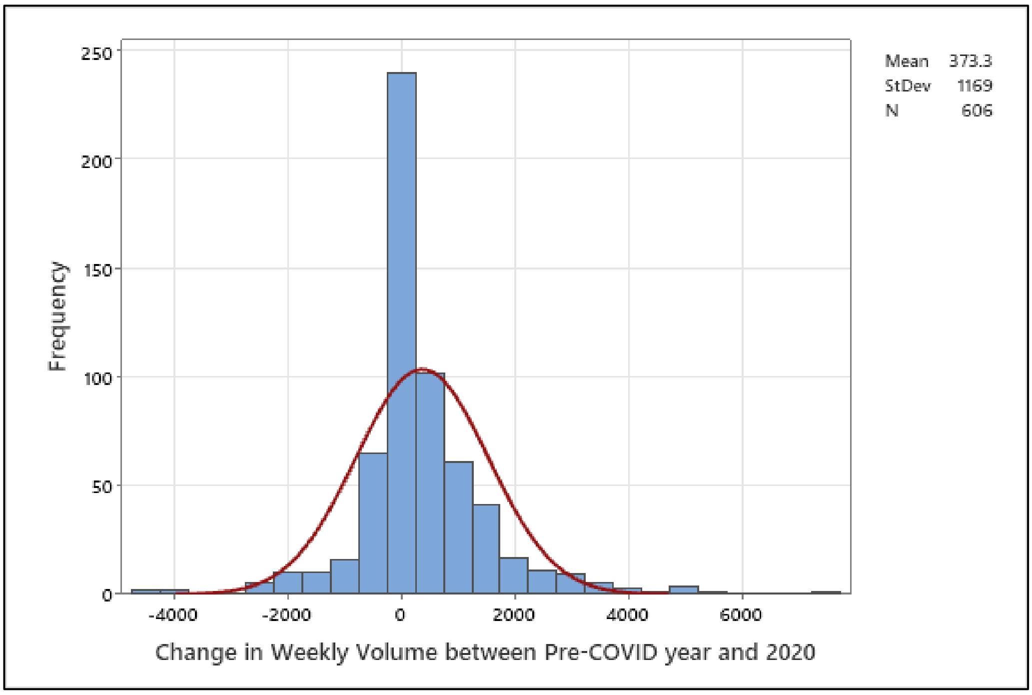

Figure 5.3. Distribution of change in weekly flow volumes

Breaking down the data by site, the ±95% CI about the difference in mean for each individual detector and colour coded according to the location type is plotted in Figure 5.4, expressed as a percentage of the mean. The counters exhibiting increases were mainly coastal sites, those experiencing a decrease were in the city areas and those showing a moderate increase were the suburban cycleways and alongside suburban main roads.

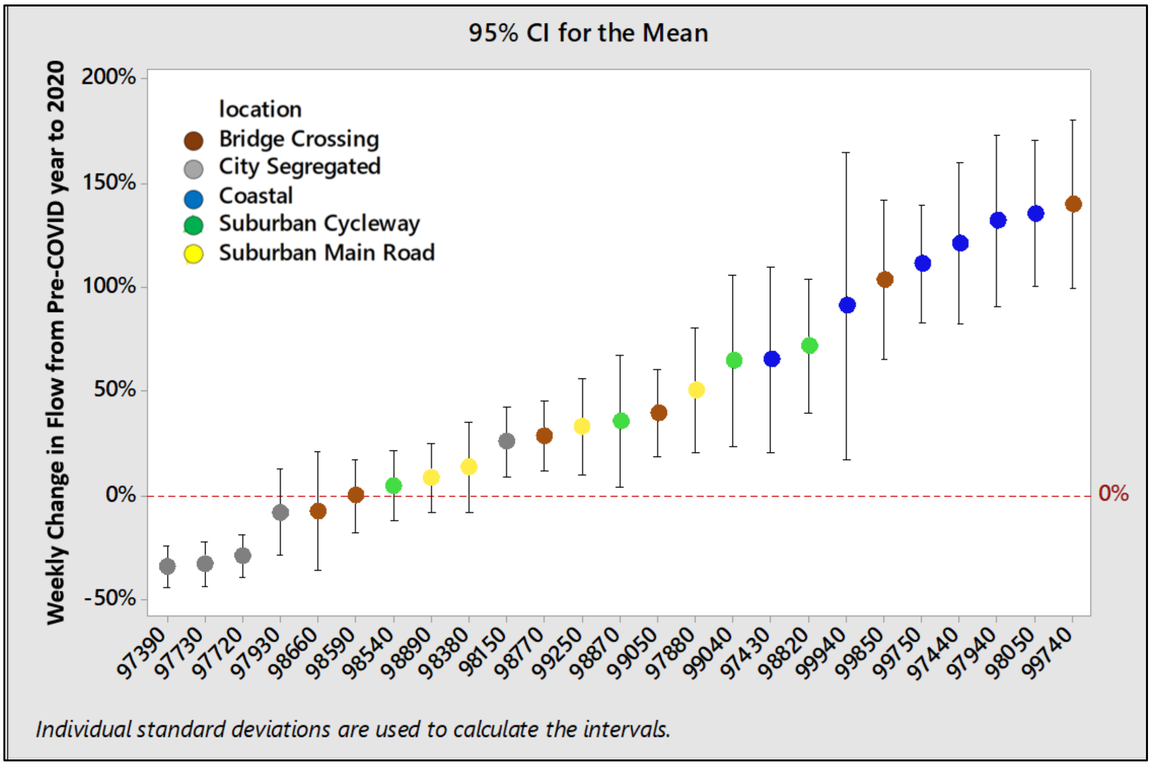

Figure 5.4. Change in average weekly flows during COVID by site

5.3 Clustering of Diurnal Flow Profiles

The clustering of daily flows identifies how the time of day and where people cycled changed during lockdown and as gradually restrictions were lifted. This is achieved by establishing similar and dissimilar characteristics in the shape of the hourly cycle flows throughout the day between 1st March and 31st August during the Pre-COVID year and 2020. When combined in one dataset there is a total of 8,741 diurnal flow profiles amounting to 209,784 hourly flows to be clustered using HCA.

5.4 Determining the Number of Clusters

Using the scree plot technique described in Section 4.6.3 suggested that the optimal number of clusters for the data lay between two and eight (see Figure 5.5). In order to identify the optimal number of clusters, HCA was performed systematically from two up to eight clustering groups. Five clusters were found to be most appropriate considering a trade-off between reducing the variation in flow profiles within each cluster, but avoiding smaller, more niche clusters that would make interpretation of the results difficult.

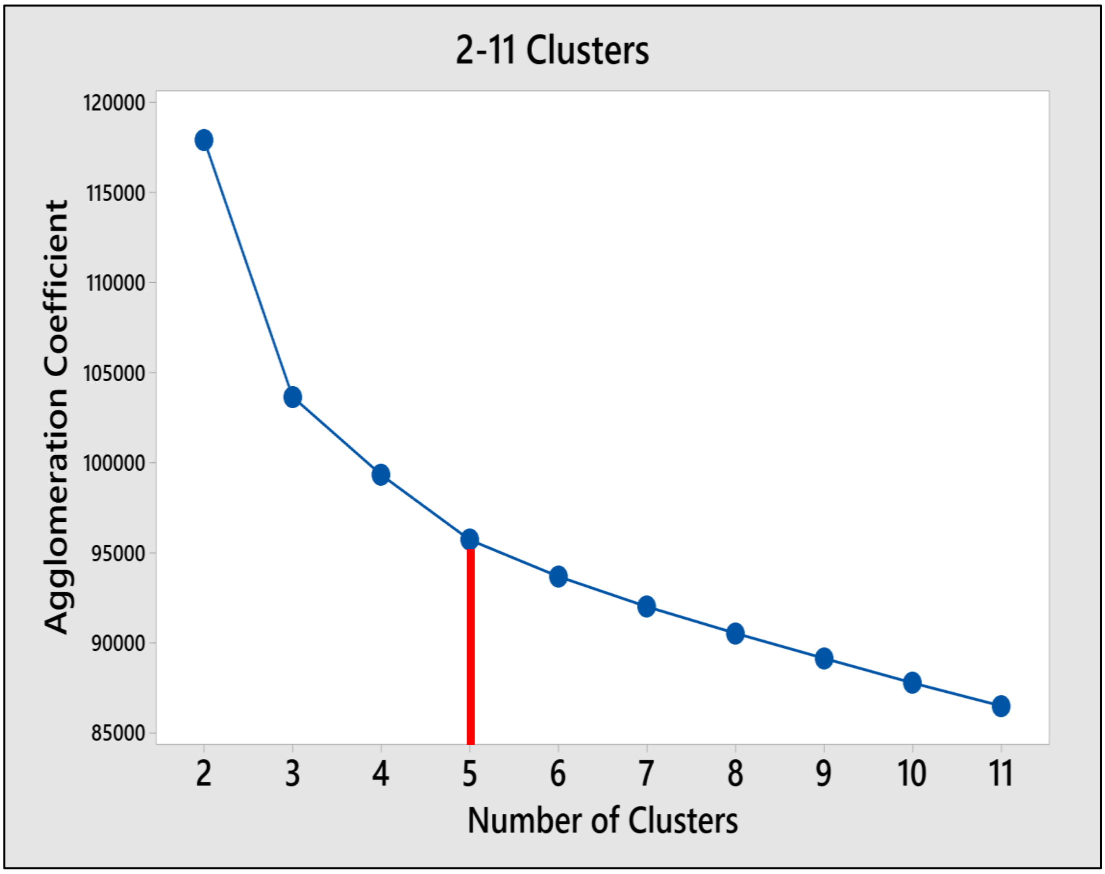

Figure 5.5. Within Sum of Squares of 2-11 cluster solution

During agglomerative HCA, the daily flow profiles are categorised into a marginally decreasing number of clusters, the final six stages of which can be followed starting at the bottom of Figure 5.6 and working upwards. Clusters are highlighted in red that join together in the next agglomeration step. Whilst the clustering process works from the bottom up, it can be easier to think of the next step in reverse of the agglomeration schedule, i.e., from the top of Figure 5.6 downwards. By doing this, it can be seen that by increasing the number of clusters from five to six the cluster of 2,674 flows splits into two: one cluster of 2,445 flows and the other with 229. It is at this point subjectively it is judged that the separation of less than 3% of the total number of diurnal profiles into a cluster was not justified when other cluster memberships were in excess of 10% and up to 28% therefore five clusters were adopted.

No. of Clusters	Number of Diurnal Flow Profiles Within Each Cluster
1	8,741
2	4,070; 4,671
3	4,070; 2,674; 1,997
4	1,797; 2,273; 2,674; 1,997
5	1,797; 2,273; 2,674; 1,063; 934
6	1,797; 2,273; 2,445; 229; 1,063; 934

Figure 5.6. Cluster Membership for 1-6 Clusters

5.5 Characterising the Clusters

Once the number of clusters for the analysis and the membership has been determined they must be given an identity in order for meaningful interpretation. Cycle use is governed by the purpose of the trip which in turn influences the time of day when trips are made. As each cluster is defined by the dominance of the shape of the diurnal profile, trip purpose will be influencing cluster membership, i.e., whether commuting or non-commuting. In this section the characteristics of daily flows within each cluster are explored, shown in Figure 5.7.

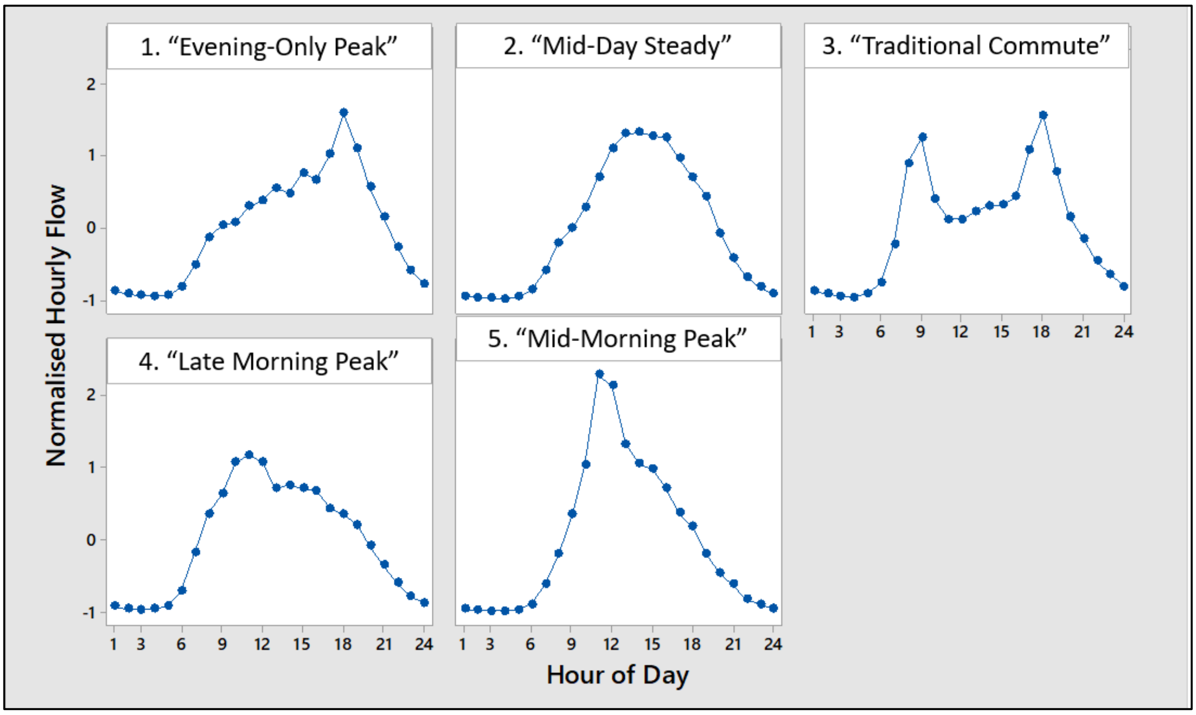

Figure 5.7. Average daily flow profile of each cluster

5.5.1 Diurnal Profiles

With reference to Figure 5.7, Cluster 1 exhibits an increase to a peak at 17:00h and a rapid fall whilst Cluster 2 shows a gradual rise in the morning up to noon and then a flattening before gradually falling after 16:00h. Cluster 3 is typical of a commute profile with a morning peak period from 06:00h-09:00h and evening peak 15:00h-18:00h. Cluster 4 exhibits a rise to a peak at 10:00h-12:00h and a gradual fall whilst Cluster 5 rises rapidly peaking at 10:00h and falls reaching zero at midnight.

The clusters have been given titles according to these characteristics, Cluster 1, 2, 3, 4 and 5 are named respectively Evening-Only Peak; Mid-Day steady; Traditional Commute; Late Morning Peak and Mid-Morning Peak. Table 7 provides an overview of the characteristics of the diurnal flows associated with each cluster which will be discussed in the remainder of this section.

Table 7. Overview of the Characteristics of Each Cluster

Value	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Defining Shape	Evening-Only Peak	Mid-Day Steady	Tradition al Commute	Late Morning Peak	Mid-Morning Peak
Total No. of Daily Counts	1797	2674	2273	1063	934
% of All Counts (nearest 1%)	21%	31%	26%	12%	11%
Year					
Pre-COVID year	52%	39%	59%	54%	48%
2020	48%	61%	41%	46%	52%
TOTAL	**100%**	**100%**	**100%**	**100%**	**100%**
Day of Week					
Monday	16%	15%	17%	10%	8%
Tuesday	15%	11%	21%	14%	6%
Wednesday	15%	12%	19%	14%	5%
Thursday	15%	12%	19%	14%	9%
Friday	10%	14%	17%	17%	13%
Saturday	15%	19%	4%	16%	24%
Sunday	14%	17%	3%	15%	35%
TOTAL	**100%**	**100%**	**100%**	**100%**	**100%**
Counter Location					
Coastal	16%	32%	4%	33%	50%
City	29%	15%	36%	5%	5%
Bridge Crossing	28%	19%	31%	24%	18%
Suburban cycleway	17%	24%	9%	9%	13%
Suburban Main Road	10%	10%	20%	29%	14%
TOTAL	**100%**	**100%**	**100%**	**100%**	**100%**
Notable Periods of Lockdown Restriction and Easing					
Pre-COVID Lockdown Pre-26 March 2020	57%	45%	67%	60%	61%
Full Lockdown 26 March - 10 May 2020	9%	21%	8%	9%	16%
Return to Work 11 May – 31 May 2020	5%	8%	4%	5%	6%
Partial School Reopening 1 June - 3 July 2020	10%	10%	9%	8%	4%
Hospitality Reopening 4 July – 31 Aug 2020	19%	16%	13%	18%	12%
TOTAL	**100%**	**100%**	**100%**	**100%**	**100%**

5.5.2 Cluster Membership across Pre-COVID year and 2020

The number of daily profiles categorised in each Cluster was established, with most falling in the Mid-Day Steady (31%) and Traditional Commute (26%) followed by Evening-Only Peak (21%). Mid-Morning peak (11%) and Mid-Day Steady (12%) had substantially fewer. But generally, the clusters are of similar magnitude, a trait of Ward's Method.

Table 8 shows that two of the five flow profile clusters are less evenly distributed across the Pre-COVID year and 2020 than the other three profiles. 39% of the Mid-Day Steady Cluster flows occurred in the Pre-COVID year with the other 61% in 2020. The Traditional Commute Cluster saw the reverse of this trend, with 59% in the Pre-COVID year and 41% in 2020. The Clusters defined by the Evening-Only Peak, Late Morning Peak and Mid-Morning Peak are represented by a more even split of Pre-COVID and 2020 days. This suggests that the characteristics of the journeys made by bicycle changed rather than just the overall volume of trips changing between the two time periods endorsing the value of the further temporal disaggregation.

5.5.3 Days of the Week

Table 7 shows each cluster comprises of different proportions of days of the week, so to gain a richer understanding the data was plotted in Figure 5.8 to show the number of days that fall into each cluster a) during Pre-COVID year and b) during 2020. Whilst the 'Mid-day Steady' and 'Late Morning Peak' profiles have slightly more weekend days clustered within them compared to weekdays, it is the Cluster characterised by the Mid-Morning peak' profile that is influenced the strongest by weekends, suggesting it is the least associated with a typical weekday commute. Conversely, the Traditional Commute cluster is strongly influenced by the weekday flow profiles, with higher number of Pre-COVID compared to 2020 during COVID, as expected as people WFH. 'Evening-Only Peak' shows a slight fall during COVID compared to Pre-COVID.

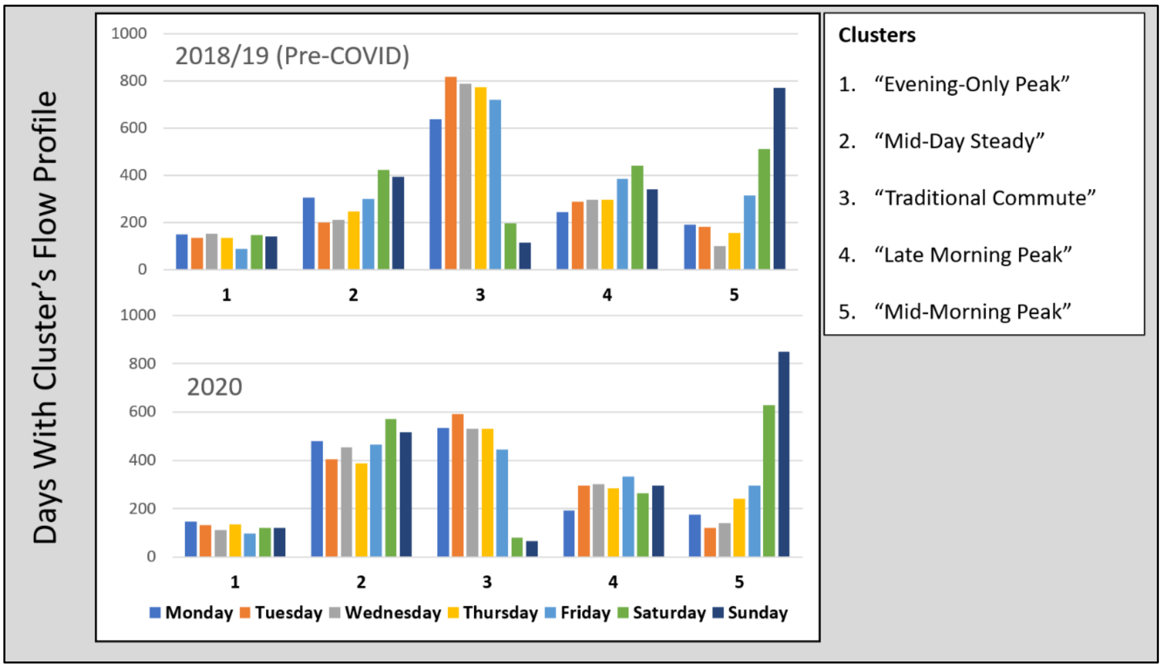

Figure 5.8. Cluster composition by day of week

5.5.4 Location of Counter

The next step was to investigate how the composition of the cluster changes with location of the cycle detector site as shown in Figure 5.9. The Traditional Commute and Evening-Only Peak clusters contained diurnal flows from mostly City Centre or Bridge locations, whilst Mid-Day Steady, Late Morning Peak and Mid-Morning Peak were predominantly Coastal. Worthy of note is the substantial lack of City locations in Late Morning Peak and Mid-Morning Peak. The descriptive statistics in Table 7 indicate that the characteristics of the city locations are different to those at the Coast, which is consistent with the differences found in the shape of the diurnal hourly cycle flows.

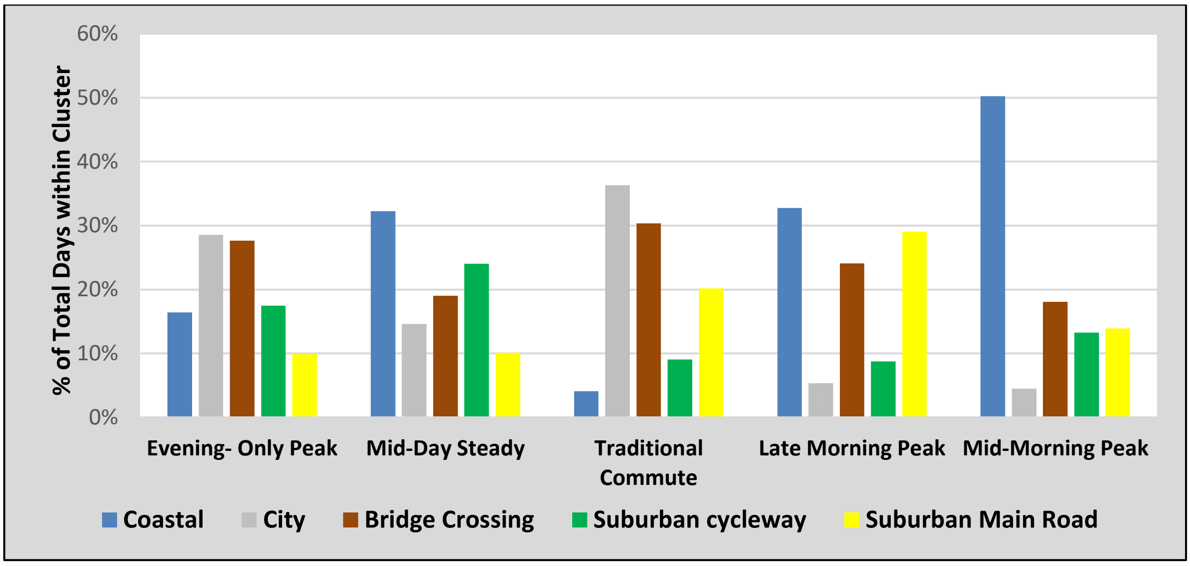

Figure 5.9. Cluster composition by counter location

The data was disaggregated according to stage of lockdown, characterised by what particular activities were forbidden or allowed in that time period. The impact the gradual easing of restrictions had on the prevalence of each daily flow profile could then be investigated, as shown in Figure 5.10.

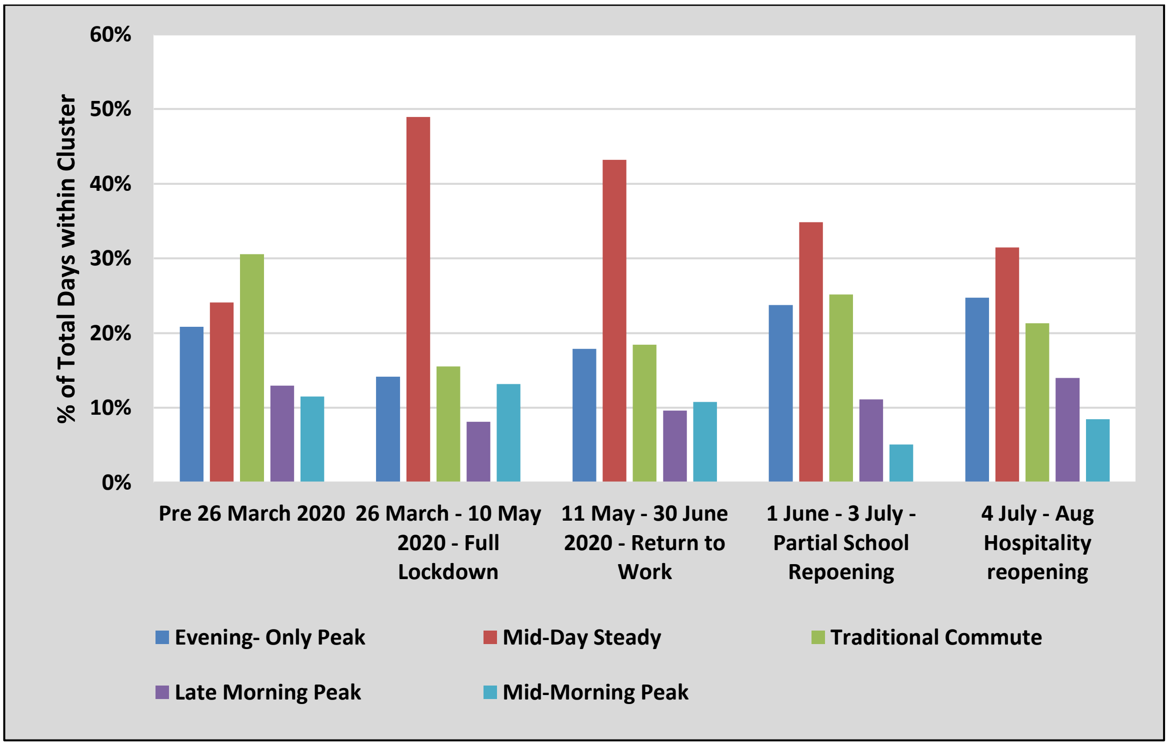

Figure 5.10. Changing flow profiles during each stage of lockdown

The Mid-Day Steady cluster approximately doubled in prevalence from 24% of total Pre-COVID flows to 49% during COVID time. As people returned to work, shops, schools and hospitality opens, the proportion declines, although still higher than pre-lockdown levels at 31% of the total between the 4th of July until the end of August.

This suggests that it is not solely due to lack of alternative recreational activities that led people to cycle proportionately more at these times, as almost every recreational activity was available once more and people were still choosing to cycle. This could either be a purely recreational cycle ride or people may have discovered cycling during lockdown as a viable mode that they wish to cycle to the reopened cafes, theatres and other re-opened services.

The opposite occurs to the Traditional Commute cycle flow profile cluster. Pre-COVID it is the dominant flow profile, representing 31% of the daily flows before dropping to 16% during full lockdown. It gradually increases in prevalence as life returns to the 'new-normal' but never reaches pre-lockdown levels as people continue to WFH, peaking at 25% of total flows before dipping slightly in August. In the UK, August typically experiences lower volumes of commuting traffic due to the school summer holidays (DfT, 2020c), which explains the reduction in the Traditional Commuting flow profiles during this time despite hospitality opening up. A similar pattern of changes occurs for the Evening-Only Cluster. Diurnal flows associated with these clusters fall from 21% of the total before lockdown measures to 14% during lockdown and gradually increases as restrictions are eased. However, where it differs from the Traditional Commute is that it continues to increase throughout August, even reaching higher proportions compared to pre-lockdown at 25% of the total flows. These flows could be a result of recreational rides returning to evenings as people return to conventional working practices and commutes into work.

The Late Morning Peak cluster sees a similar pattern to the Evening-Only Peak, one suggestion is that both flow profiles are associated with new commuting practices post-lockdown. The Evening-Only peak shows a steady flow of cyclists throughout the day, which could be people adopting new working practices where it is not essential to get to the office by 9am, however they still wish to return at a conventional commute time in the evening for dinner with family. The changes in the Late Morning peak could theoretically be this in the reverse order, coming in for a morning meeting, again without the urgency of a 9am start, but then disappearing before the traditional 5pm finish.

Finally, the prevalence of Mid-Morning Peak flows maintained relatively stable between 11-13% of the total flows up until the partial reopening of schools, where it dropped to 5%. One possible explanation for this drop could be the integration of the school run with a traditional morning commute time, as a rise in the prevalence of the Traditional Commute during the partial school reopening phase coincides with the reduction in Mid-Morning Peak flow profiles. Some individuals may have been reluctant to return to work for the usual 9am start, but once it was necessary to be out the house for the school run at that time it made more sense to link trips.

5.6 Integration of Outputs

The final step in this analysis was to link the prevalence of each clustered flow profile with change in total flow volumes during COVID, disaggregated by location. Each graph within Figure 5.11 represents one of the five clustered flow profiles. The percentage change in flow is plotted against the prevalence of each flow profile at each of the counters, calculated as the percentage each cluster appears within the total number of days recorded at each site.

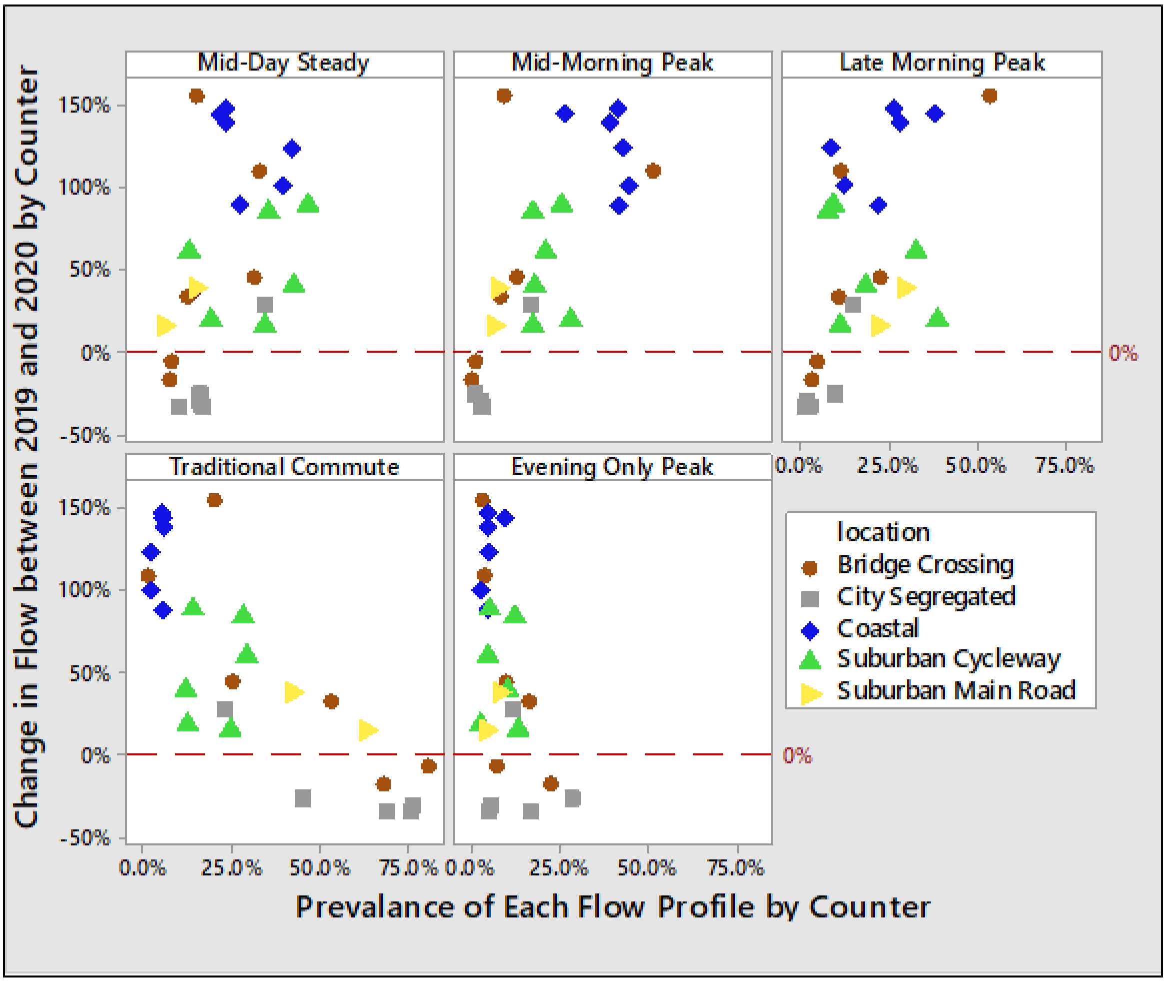

Figure 5.11. Cluster prevalence at each counter and the change in total flow

Sites with a higher prevalence of Mid-Morning Peak flow profile tended to experience the greatest increase in flow volume, with Late Morning Peak and Mid-Day Steady also associated with substantial increases. It can be seen that the counters at Coastal Sites tended to have the highest prevalence of these flow profiles as well as the highest increases in overall flows during COVID lockdown. In stark contrast, counters with a higher prevalence of the Traditional Commute and Evening-Only flow profiles, such as the City Centre locations, were associated with a decrease in flow, as seen within the bottom two graphs within Figure 5.11.

Suburban Cycleway and Suburban Main Roads with middle levels of penetration in all clusters all exhibited moderate levels of increase during COVID. This is consistent with Figures 5.2 and 5.4 that shows that there was an overall increase in cycling volumes generally.

The bridge crossings are associated with all levels of flow change and further scrutiny shows that the bridge crossings that tend to group with the coastal counters cross the River Wear (99750, 99850 and 99050 in Figure 5.1 & 5.4). The Wear crossing is closer to the Coast as well as a riverside cycleway, suggesting it could be recreational routes driving their demand. In contrast the Bridge Crossings over the River Tyne (97930 and 98590 on Figure 5.1 & 5.4) display similar qualities to the City locations, with substantial reductions in cycle flows, being much closer to the Newcastle City Centre and historically cater more for commuters.

5.7 Discussion

5.7.1 Suitability of Hierarchical Cluster Analysis of Cycle Flow Profiles

Whilst previous use of HCA has focused on flow profiles of motorised vehicles, this research has demonstrated, by studying the impact of COVID-19 on bicycle flows, that HCA is a flexible tool that can be used in a wide range of flow types, locations and to quantify the impact of new situations of which we had no previous experience. By obtaining valuable results without pre-classifying the data as per previous studies (Weijermars & Van Berkum, 2005), the flexibility of this methodology is demonstrated further. This paves the way to testing the methodology on subsequent data sets. Though this study looked at the impact of COVID-19, future uses could assess the impact on both cycle and motorised vehicle flows with the introduction of policy measures aimed at achieving a ‘Green Recovery’ or net zero, such as Low Traffic Neighbourhoods, Clean Air Zones or active travel infrastructure investment. The more evidence decision makers have available to them, the more understanding they possess when making key decisions regarding controversial schemes (Aldred et al., 2019).

HCA proved to be effective in predicting whether a flow profile was strongly associated with commuting or non-commuting purposes. The assignment of Cluster 3 as the “traditional commute” profile was validated when the results revealed that this shape was most prevalent mid-week, in the city centre closest to the region’s CBD and experienced the greatest reduction as society was instructed to WFH. Even with further disaggregation of the data, it was not possible to definitively say what trip purposes were defining the other shapes, although it is considered they are recreational or non-commuting in nature. Further research is required beyond this to determine HCA’s suitability to infer more detail of a non-commuting trip by flow profile alone.

Whilst basic descriptive statistics, such as the change in flow volume, gives some insight into patterns of cycling flows within large datasets, HCA of hourly flows can complement this by also interpreting diurnal flow profiles. With this methodology, practitioners have an additional tool to monitor and characterise cycling flows during the transition into a post-pandemic era. Furthermore, the method shows promise to evaluate in a consistent way changes that may result from investment in active travel or changes in policy, low emission zones, safe routes to school, workplace schemes or similar.

5.7.2 Changing Cycling Flow Patterns during COVID-19

The results from this research align with the UK Government’s position that the pandemic resulted in “unprecedented” levels of cycling. Notably, flow profiles associated with non-commuting trips across Tyne and Wear increased throughout the period of COVID-19 restrictions, particularly those near coastal and suburban areas. This is consistent with the Glaswegian study into the early stages of lockdown conducted by Hong et al, (2020). In terms of policy implication, these trips contribute significantly towards the target set out in the UK Cycling and Walking Investment Strategy to double cycling trips from 2013 levels by 2025 (Jones, 2019). As the target does not discriminate according to journey purpose, maintaining and growing these trips will remain important following the pandemic, particularly if the shift in culture to WFH becomes permanent. Any trips, once carried out by car that are replaced by bicycle will be a positive contribution to achieving the wider sustainability policies outlined in Chapter 2, such as achieving Net Zero.

Throughout the duration of the COVID-19 restrictions, substantial increases in cycling were seen in flows grouped in the Mid-Day Steady Peak, reaching its highest in the full lockdown period, consistent with non-commuting trips such as recreation or visiting shops. By disaggregating the data by notable periods of lockdown and restrictions easing, it reveals the Mid-Morning Peak, Late Morning Peak and Evening-Only clusters increased when hospitality re-opened, which we can speculate is consistent with non-commuting activities such as morning coffee or lunch and socialising in the evening. Weekends in Pre-COVID days and days after the hospitality sector re-opening in 2020 were dominant in the Mid-Morning Peak, which suggests it may be associated with shopping and socialising during the day in cafes, bars and restaurants.

Suburban cycleways consistently fall in the medium prevalence of all the clusters with moderate increase in flows during COVID relative to Pre-COVID. This suggests that suburban cycleways are used for a range of trip purposes and therefore less likely to see reductions in flows compared to their city centre counterparts as people WFH more and commute less. This potentially makes their flow volumes more resilient to future change and a safer investment when locating infrastructure or implementing schemes.

It should be noted that there were factors other than reduced motorised traffic associated with the lockdown that is reasonable to assume affected cycling volumes, such as cycling becoming one of the few recreational activities available to people at the time. However, the increase in non-commuting flows during this time, when traffic volumes were up to 63% lower than in the previous year, suggests the possibility of suppressed demand for cycling within the case study area that was only realised once the perception of danger associated with cycling amongst other traffic was decreased. These findings are consistent with a key intervention outlined in the North East’s Local Transport Plan; the creation of safe, segregated routes for cycling, formed in line with national Government guidance and described in the case study section of Chapter 4.

Finally, the City Centre cycle counters, which were dominant in the Traditional Commute and Evening Peak profiles, showed the highest reductions in cycle flows during COVID-19, most significantly during the full lockdown period. This substantial reduction in commute trips is also consistent with Hong et al. (2020). Because a further four months (May-August 2020) were included in this research compared to the Hong et al. study, this work has extended the initial findings and observed cycle flows beyond the full lockdown period. This demonstrated that commuting trips by cycle did show signs of returning to Pre-COVID levels as lockdown was gradually eased in the subsequent months in the UK, results consistent with commuter activity within the nation-wide bike-sharing market reported in Nikitas et al. (2021).

This section has touched upon the implications for policy in terms of non-commuting cycling, however in a region such as North East England with a modest cycling culture, policies that target any growth or exposure to cycling will have a positive effect on it being a mode of choice of the commuter in the future. Whilst prior to the pandemic local authorities believed political barriers, namely the fear that their core, car-driving voters will be disillusioned by pro-cycling schemes (Aldred et al., 2019), this study contributes to the growing evidence, made possible by the pandemic, that there is a desire to cycle more when given the right conditions. Moving beyond the pandemic, the new-founded cycling advocacy will generate political will for further investment in cycling infrastructure that, if realised, will be inclusive in that all types of cyclists will benefit to some extent.

5.7.3 Opportunities for Further Study

Relating these findings back to Nikitas et al. (2021), many emergency cycling infrastructure schemes failed due to lack of understanding of the needs of the users, possessing this additional information regarding flow profile enables transport planners to decide whether to prioritise direct, faster routes (i.e., for regular commuters), or safety and segregation to attract the less confident, non-commuters from a wider socio-demographic background (Dissanayake, 2017; Steinbach et al., 2011; Rossetti et al., 2019; Kircher et al., 2018; Broach et al., 2012). Future research of a qualitative nature could be conducted considering the findings presented in this manuscript. Surveys and focus groups could identify the characteristics of the people, the specific trip purposes and the cycling conditions that contributed to the increased cycling volumes experienced during the 2020 lockdown, particularly during the Mid-Morning Peak period which was found in this study to experience the greatest increase in cyclist flows. As we move into the New Norm and given the number of new cyclists, it would be useful to understand motivation and to co-create interventions that would encourage them to continue to cycle post-pandemic. Identifying future cycling infrastructure projects in this way maximises the benefits of local authority investment at a time of budget constraints. In addition, understanding the barriers to cycling of the general population would be useful to encourage a mode shift from private vehicle use as local governments continue to invest in infrastructure.

On the subject of identifying active travel infrastructure investment, one of the sites analysed was Beverley Terrace in Cullercoats where coincidently the inductive loop detector already in situ recorded the activity along the “Sunrise Cycleway” an EATF scheme consisting of a 3km segregated pop-up, two-way cycle lane between the North Tyneside seaside towns Whitley Bay and Tynemouth, shown in Figure 5.12. The coastal road was reduced to southbound only traffic, with the northbound lane becoming a two-way cycle lane. Despite a shared-use path already in existence, the increased volume of pedestrians and cyclists at the coast meant that maintaining social distancing and safely catering for both cyclists and pedestrians was deemed impossible.

Figure 5.12. Sunrise Cycleway (NEJTC, 2021)

The wider investigation of the region within this study revealed that the Sunrise Cycleway was appropriately implemented where some of the largest increases in cycling volumes were measured. Moreover, reallocating the southbound carriageway from motorists to cyclists was effective in maintaining the increased cyclist volumes whilst creating more space for pedestrian social distancing on the original shared use path. However, when it was opened in July 2020 it did not appear to attract more cyclists than were already using the shared-use pavement facilities in the earlier months of lockdown. Possibly this was due to the peak of cycling having already passed.

5.7.4 Limitations

Within the data preparation stage of the research, it was necessary to substitute missing data in 2019 flows with 2018 where inductive loop counters had not recorded data sufficiently. This represented 5.64% of the total data set. Given the slow uptake of cycling in the UK the difference in flows between 2018 and 2019 are small (0.5% decrease in North East England), therefore dealing with missing values in this way was considered acceptable, particularly when considering the substantial differences witnessed during 2020 compared to any other previous year in recent history.

Whilst it has been demonstrated that this methodology is able to quantify the changes in the shape of diurnal flow profiles, the causation remains unknown. A traditional daily commuting flow profile is instantly identifiable by a morning and evening peak; however, it is not possible to infer the trip purpose beyond commuting / non-commuting with flow profiles alone. Whilst the changes to lockdown restrictions provided some insight into how the trip profiles changed as different sectors re-opened, without asking a cyclist specifically the purpose of their trip it is not possible to know. The dataset consisted of 25 counters recording hourly cycling flows, 24 hours a day, across two eight-month periods therefore collecting trip purpose information is clearly outside the scope of this high-level study. However, carrying out a survey over a limited number of days would make for an interesting study into how trip purpose changes across the week and non-weekdays, as would the qualitative research, described in the previous section.

5.8 Chapter Conclusion

The green recovery from the COVID-19 pandemic will require bold, significant interventions in order to achieve Net Zero. Cycling will play a part in decarbonising transport, however previous literature states that there is a risk of public backlash from ill thought-out schemes designed to improve cycling, both before the pandemic and during it. This study provides a methodology to quantify changes to flow profiles in large datasets that can be used as an additional tool to complement standard descriptive statistics and aid the decision-making process. The following main conclusions can be drawn from this research:

- The flexibility of cluster analysis has been demonstrated and it can be transferred to any location with appropriate flow data and used to quantify the impact on cycle flows of relatively unknown situations, the example presented in this research being the COVID-19 pandemic lockdown;
- The overall volume of cycling increased substantially (add %) across the case study area of Tyne and Wear as a result of UK Government-implemented lockdown restrictions, as experienced in previous studies;
- HCA of daily flow profiles and subsequent disaggregation of the data provides decision-makers additional insight into changes in cycling patterns beyond looking only at changes in flow volume, with it a better understanding of the composition of journey types on a route that can be taken into consideration when implementing new schemes;
- Non-commuting flow profiles witnessed the largest increase during lockdown, in locations closer to suburban or recreational opportunities, therefore planners should consider catering for cyclists making such trips in these locations in order to maintain cycling levels after the pandemic. This can be achieved by valuing safety through segregation from vehicular traffic over the fastest, shortest and safest route; and
- As lockdown restrictions eased, flow profiles began to revert back to the pre-pandemic norm, although they never returned even with all restrictions eased. Planners will need to pay close attention to whether the shift to WFH is maintained after the COVID-19 pandemic is behind us and the associated cycling flows remain.

Finally, this study demonstrates that substantial increases in cycling flows can be achieved given the right conditions. Whilst the increased popularity of cycling during the pandemic had short-term benefits, the consequential increased cycling advocacy and political will potentially contributes to longer term cycling policy aims, paving the way for more ambitious investment in cycling infrastructure that will benefit all cyclist and trip purposes. Adopting a similar methodology as this chapter, the next chapter will analyse the impact of such investment brought about by the EATF allocation in the Tyne and Wear case study area.

Chapter 6. Low Traffic Measures and Post-Pandemic Active Travel

6.1 Introduction

Study 1 found that during the lockdown, Tyne and Wear experienced similar increases in cycling levels found in other parts of the country and across the globe identified in the literature review chapter. Like many parts of the world there was a need to provide ‘pop-up’ infrastructure to accommodate these additional cyclists as well as pedestrians whilst facilitating social distancing. The Emergency Active Travel Fund (EATF) provided the opportunity for local authorities to implement such measures, with additional funding in the following post-pandemic years to make such measures permanent. The literature review chapter also highlighted the uncertainty as to whether the daily patterns in active travel would remain in the post-pandemic era whilst also identifying the negative impact of poorly implemented pop-up infrastructure. One of the incidental findings within Study 1 was that the only counter of the 25 that was coincidentally located within an EATF schemes, namely Beverley Terrace in Cullercoats, experienced the greatest increases in cycling volumes during the pandemic. For these reasons, there is a need for a study that takes a specific interest in more locations where these interventions occurred, and to see how they also performed after the pandemic.

This chapter presents the results and discussion of the second of three studies that comprise this thesis. Study 2 builds on the findings of Study 1 in four main ways. Firstly, with the passing of time it was possible to analyse data further into the post-pandemic period, in this case up to March 2022, whereas the first earlier study was only able to compare lockdown flows with pre-pandemic flows. Study 1 focused on the change in travel behaviour resulting from government-enforced lockdown periods with varying levels of severity, finding that the most dramatic change in cycling volumes and diurnal flow profiles occurred early in the lockdown when restrictions were most severe. There was evidence to suggest that as restrictions were lifted, the diurnal flow profiles began to return partially to pre-pandemic patterns. With the benefit of a full year of post-pandemic data, Study 2 examined the lasting effects of the pandemic that was not possible in Study 1.

The second main difference to the previous study is the targeting of sites where EATF measures had since been made permanent. Low traffic neighbourhoods (LTN) have become a common term used for these schemes, and whilst they existed prior to the pandemic, the implementation of LTNs since COVID has been accelerated and remains a key tool to encouraging active travel. As identified in the literature review prior to the pandemic, LTNs were often met with opposition (Aldred et al., 2019). For this reason, it was considered important to research how they are being used in the post-pandemic era to provide additional information to decision-makers as to whether they remain beneficial after the lockdown-era active travel boom.

Thirdly, instead of conventional inductive loop detectors, data was collected using Machine Vision Cameras (MVC) able to capture both cycle and pedestrian flows, offering an opportunity to compare pedestrian flows with cycling and the need to develop new skills to perform cluster analysis using R instead of SPSS to manage the increase in volume of data.

The next section will describe the sites chosen for analysis; Section 6.3 then outlines the methodology. The changes in flow volumes are presented in Section 6.4 whilst the results of the clustering of the diurnal flow profiles are presented in Sections 6.5-6.7. Section 6.8 identifies the potential effect of the lifting of lockdown and the prominence of a student population on active travel flows before the implications of the results are discussed (Section 6.9) and the chapter is concluded (6.10).

6.2 EATF Sites

Data was collected at five sites where MVC were available to automatically detect multi-modal flows and ideal for capturing both pedestrians and cyclists. The sites consist of five small bridges located across Newcastle upon Tyne, UK that saw bans on motorised transport during lockdown using the EATF. These traffic reduction measures have subsequently been made permanent after the success of the temporary trials during lockdown as they meet NCC’s ambition to make local neighbourhoods cleaner and safer by reducing through-traffic within residential areas.

After seeing the first lockdown restrictions lifted in July 2020, Newcastle experienced a second round of full lockdown restrictions between 14th October 2020 and 7th March 2021, due this time being under either national lockdown or “tier 3” (very high risk) local lockdown conditions. Through this period, society was once again expected to work from home whilst schools, non-essential retail and hospitality were closed. Hourly cycling and pedestrian flows were captured during this second lockdown and compared to the same period one year later once restrictions were fully lifted (14th October 2021 to 7th March 2022).

Study 1 took an overview of the wider Tyne and Wear region, consisting of 25 cycle counters. As Study 2 targets EATF sites, a substantially smaller number of sites were chosen, allowing the data from each one to be analysed in more detail, identifying their specific nuances. Their locations are shown in Figure 6.1 and are as follows, heading north from the River Tyne:

1. **Argyle Street Bridge, Ouseburn**. Closest to the City Centre surrounded by student accommodation and part of the University campus. Nightlife spots the Quayside and Ouseburn lie to the south and east, respectively;

2. **Haldane Bridge, Haldane Terrace, Jesmond**. Part of a route into the City Centre within inner city suburb. The area is popular with students and close to schools and the busy high street Osborne Road;

3. **Dene Bridge, Castles Farm Road, South Gosforth**. Further from the City Centre than the previous sites, cuts through Jesmond Dene, a local park;

4. **Stoneyhurst Road Bridge, South Gosforth**. Residential area further away from the City Centre;

5. **Salters Bridge, Gosforth**. The site furthest from the city centre. Recreational paths are located nearby with residential estate situated to the west of the bridge.

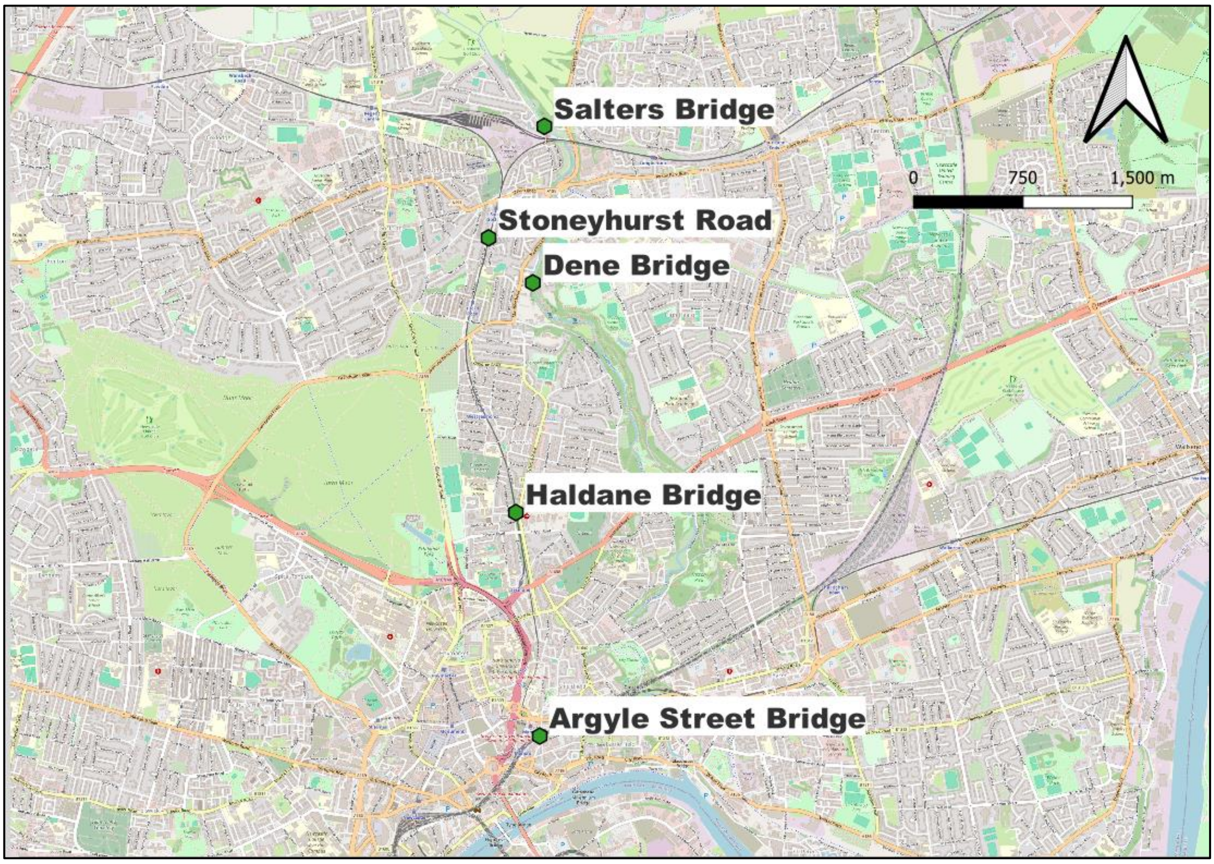

Figure 6.1. Five site locations across Newcastle upon Tyne

Experimental traffic regulation orders were used to install modal filters on the bridges, prohibiting motorised vehicles. They remained open to cyclists and pedestrians, providing a safe and convenient route for people in and around their local area. Figures 6.2 – 6.11 were obtained from the Newcastle safe bridges website (Newcastle City Council, 2021), and are computer-generated images of the schemes that accurately reflect what was installed.

6.2.1 Argyle Street Bridge, Ouseburn

Argyle Street Bridge (see Figures 6.2 and Figure 6.3) provides a link over the East Coast Mainline between the Primary Distributor Road A193 Newbridge Street and the Quayside / Ouseburn areas of Newcastle upon Tyne. Just 150m west on the A193 is a grade-separated junction with the A167(M) and the main routes north and south out of Newcastle. From a public transport perspective, the nearest Metro Station is Manors, which also serves regional national rail services, is only 100m away and could account for a significant number of movements across the bridge. The nearest bus stop is 100m north on Newbridge Street served by an abundance of frequent services.

For pedestrians and cyclists, the bridge provides a key link between popular hospitality areas of the Quayside and Ouseburn with the City Centre. It also provides a link to Northumbria University Business School with several large blocks of student accommodation. It is worth noting that students make up 61% of the population of the Ouseburn ward (Nomis, 2022). Argyle Street to the south of the bridge is notably steep, heading downhill south. According to the 2021 Census, driving (25%), walking (21%) and bus (10%) are the most common modes of commuting from the Ouseburn Ward (Nomis, 2022). It is worth noting the census was recorded during the pandemic and a significant amount of people stated they did not commute, working from home instead.

Figure 6.2 Argyle Street before Low Traffic Measures (Newcastle City Council, 2021).

Figure 6.3 Argyle Street after Low Traffic Measures (Newcastle City Council, 2021).

6.2.2 Haldane Bridge, Haldane Terrace, Jesmond

Haldane Bridge is a single-carriageway with a 10T weight and 20mph speed restriction prior to the interventions. There are footpaths either side (see Figures 6.4 and 6.5). The bridge spans the Tyne and Wear Metro line between Jesmond and West Jesmond stations, 450m and 750m away, respectively. The Metro offers links to city centre, Central Station for national rail, The Coast and Newcastle Airport. Bus services are available nearby on Osborne Road. In terms of road connections, a junction between major distributors the A1058 and A167(M) is 400m south of the bridge, providing links to the North East region and beyond.

Similar to Argyle Street, the area is popular with students, which make up just over 50% of the population of the South Jesmond Ward that Haldane Bridge is situated within (Nomis, 2022). It also contains several schools, many of which are private, which generate peak-hour traffic in the area. Haldane Bridge is in the centre of a high pedestrian and cyclist activity area in close proximity to the City Centre and the busy Osborne Road lined with bars and restaurants. Haldane Bridge is 130m north of the segregated, two-way cycle lanes along Eslington Terrace that provides onwards segregated cycling links to the City Centre. Prior to the measures the narrow bridge provided insufficient capacity for pedestrians, particularly for the disabled and those pushing prams. This issue is especially relevant within the South Jesmond Ward as walking is nearly as common as driving when commuting in South Jesmond, contributing to 20% and 26% of total residents travel to work. Surprisingly, cycling contributes just over 3% (Nomis, 2022).

Figure 6.4 Haldane Bridge before Low Traffic Measures (Newcastle City Council, 2021).

Figure 6.5 Haldane Bridge after Measures (Newcastle City Council, 2021).

6.2.3 Dene Bridge, Castles Farm Road, South Gosforth

Dene Bridge (see Figures 6.6 and 6.7) connects the heavily trafficked Primary Distributor Road Matthew Bank in South Gosforth to Secondary Distributor Road Freeman Road in High Heaton, which both possess bus stops with frequent services, and spans the popular walking and cycling area of Jesmond Dene. Often used as a cut-through between the two roads, the bridge itself is narrow and requires weight restrictions. Motorised traffic could only flow in one direction at a given time prior to the modal filters, operating with a give-way system. There was no infrastructure for cyclists or pedestrians, creating a major barrier to potential active travel users, specifically when considering the proximity to Jesmond Dene, a destination for recreational walks and cycles as well as providing a segregated route into the city.

Figure 6.6 Dene Bridge before Low Traffic Measures (Newcastle City Council, 2021).

Figure 6.7 Dene Bridge after Low Traffic Measures (Newcastle City Council, 2021).

Given the location of Dene Bridge within Jesmond Dene, it could be expected to be a focal point for the recreational walks and cycle rides. Further away from the student centres than the Haldane and Argyle Street Bridges and with no schools in the immediate vicinity, the mix of trips are expected to be different. The nearby Freeman Hospital and HMRC offices are major employment sites and South Gosforth and high Heaton are large residential areas.

These factors lead to a different mix in terms of demographics, with 11% of the populations being students. Possibly due to the proximity of the Freeman Hospital, '"human health and social work activities" is the most common industry people within the Dene & South Gosforth Ward, contributing to 24% of all workers. Education is next (17%), followed by Public administration (9%) which could be as a result of the HMRC offices. Rather than student flats or houses of multiple occupancy, 75% of households own their own house who live in the ward (Nomis, 2022).

Being slightly further away from the city centre, this is reflected in the commuting habits with 33% using car, 11% using foot and 3.4% using bike. 42% WFH, which is larger than the previous two locations (Nomis, 2022).

6.2.4 Stoneyhurst Road Bridge, South Gosforth

Stoneyhurst Road Bridge (see Figures 6.8 and 6.9) is located in the heart of residential South Gosforth and crosses the Tyne and Wear Metro line immediately south of South Gosforth Metro Station. The area is within a comfortable walkable distance to Gosforth High Street and the closure is intended to make this an option, along with cycling, becoming safer and more attractive for these modes. Prior to the interventions, the 20mph, single carriageway could be used as a cut-through between the Matthew Bank and Gosforth High Street, which is itself a Secondary Distributor Road, a popular option for motorists wishing to avoid the infamous Haddrick's Mill roundabouts. In terms of active travel provision, pedestrians have footpaths on either side of the bridge and there is no dedicated infrastructure for cyclists.

Figure 6.8 Stoneyhurst Road Bridge before Low Traffic Measures (Newcastle City Council, 2021).

Figure 6.9 Stoneyhurst Road Bridge after Low Traffic Measures (Newcastle City Council, 2021).

Sitting in Dene & South Gosforth ward, the same as Dene Bridge, means the surrounding residential areas share a similar mix demographically, with less students. With the different services nearby including schools, popular high street as well as public transport options into town via the Metro Station, a mix of diurnal flow profiles is anticipated.

6.2.5 Salters Bridge, Gosforth

Salters Bridge (see Figures 6.10 and 6.11) is a medieval, Grade I listed bridge and the northernmost low traffic measure intervention site. With Hollywood Avenue leading to Gosforth High Street to the west and the Primary Distributor Road Killingworth Road to the east, prior to the modal filters being implemented it was a popular cut-through.

Whilst all of the low traffic measure sites experienced the negative impact of vehicle traffic to some degree, the Salter Bridge in particular suffered most due to higher traffic flows given its age. Previous monitoring of the road in 2019 found that in one week 1,000 vehicles exceeded the 3.5 tonne weight restriction and 18,000 drivers exceeded the 20mph speed limit further along Hollywood Avenue (Newcastle City Council, 2021). Generally, in a quieter area than Stoneyhurst Road, it is also a popular recreational destination similar to Dene Bridge.

Figure 6.10 Salters Bridge before Traffic Calming Measures (Newcastle City Council, 2021).

Figure 6.11 Salters Bridge after Traffic Calming Measures (Newcastle City Council, 2021).

200m to the east of Salters Bridge are the bus stops on Salters Lane, whilst South Gosforth is the closest Metro station, 550m south-west. Additionally, Regent Centre is a Metro Bus Interchange and sits 1.1km east of the bridge at the top of Gosforth High Street.

Salters Bridge is in Gosforth and sits within the Parklands ward. As well as geographically being the two furthest away sites, according to the census, Parklands and Ouseburn perhaps also have the biggest gap in demographics out of the wards within the study area. Ouseburn possesses the highest proportion of students (61%), Parklands is the lowest (6%). Conversely, Parklands has the highest proportion of retired people (28%), whilst Ouseburn had the lowest (5%). These differences in population will lead to different travel behaviour in terms of trip time, purpose and mode. Those who do work, human health and social work activities (21%) and Education (14%) are the notable professions, 24%. Entering the suburbs is reflected in the mode choice to commute, with 40% driving and 5% walking. Bicycle is 3% whilst public transport use is 5% for bus and 2% for the Metro (Nomis, 2022).

Summary of Low Traffic Measures

The sites of the five low traffic measure implementations each have their own character, as described in this section. Generally, Argyle and Haldane Bridges are located closer to the City Centre and flows are characterised by this as well as the student population. Therefore, being located closest to the employment areas of the City Centre and the Quayside, commuter-shaped profiles may be the most prominent here. On the other hand, the multiple uses associated with these areas, including retail and hospitality, mean there could be a wider mix. Stoneyhurst Road is nestled in a residential area, which could contribute towards a mix of trip types, whilst the proximity to South Gosforth Metro station may result also in the presence of commuter-shaped profiles. Finally, Dene Bridge and Salters Bridge are older bridges in quieter locations further out of the City Centre and expected to experience proportionately the highest recreational trips, which, similar to the commuting shapes, can be inferred by the shape of the diurnal flow profile.

6.3 Summary of Methodology used in Study 2

The average daily flows during and post-pandemic will be compared at each of the five sites to assess whether the change is universal or is different between sites.

Hierarchical cluster analysis was chosen over other methods, such as k-means, because the number of clusters do not have to be predefined. Euclidean distance was used to calculate the similarity between each individual diurnal flow profile, and they were subsequently clustered using Ward’s method.

Section 3.5.5 stated that z-standardisation is better suited to datasets with more variability than normalising around the mean (Nicholson et al., 2022). Section 4.4.3 outlines why variability across the day and study period is expected to be higher and therefore it was decided to use z-standardisation for Study 2.

6.4 Change in Daily Flow Volumes

With reference to Figures 6.12 and 6.13, when considering the totals across all five sites, the volumes of pedestrians are substantially higher than the cyclists generally and increasing from an average of 1,132 per site in the lockdown era to 1,371 in the post-pandemic period. With 21% increase in pedestrians cycling witnessed proportionately the greater increase of 40%, with 137 cyclists on average per site in the lockdown and 192 in the post-pandemic era.

As Study 1 found differences across each site, the distribution of daily flow volumes were plotted per site to compare during lockdown with the post-pandemic, see Figure 6.12. for pedestrians and Figure 6.13 for cyclists.

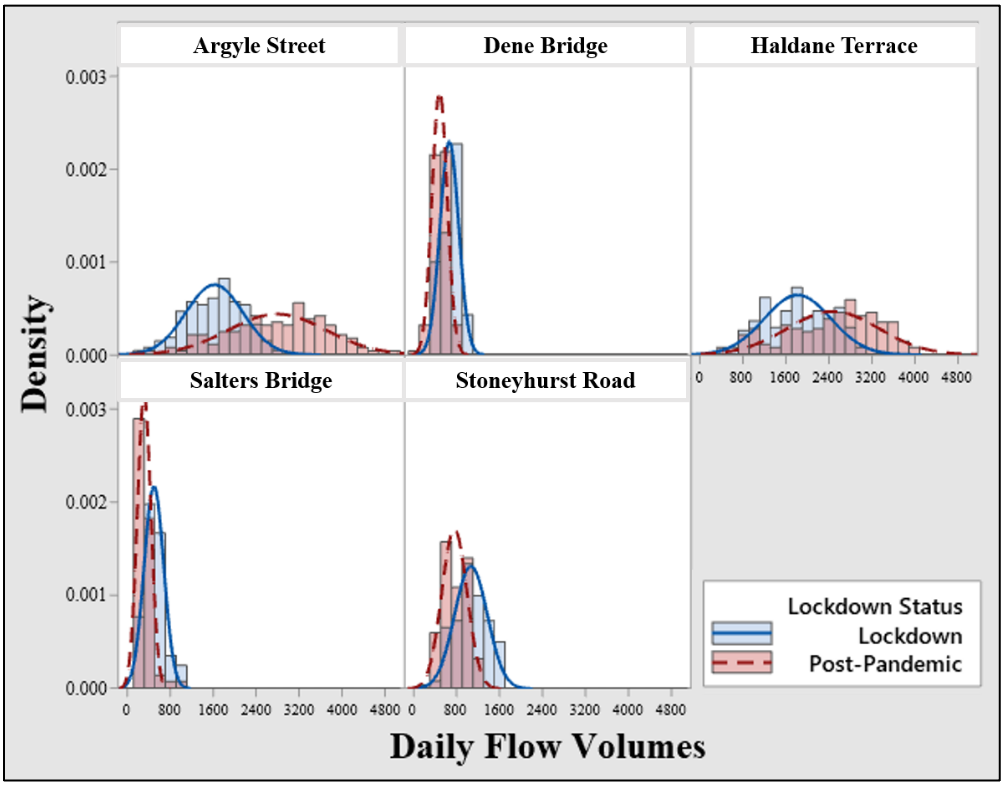

Figure 6.12. Histogram of Pedestrian Daily Total Flows by Site

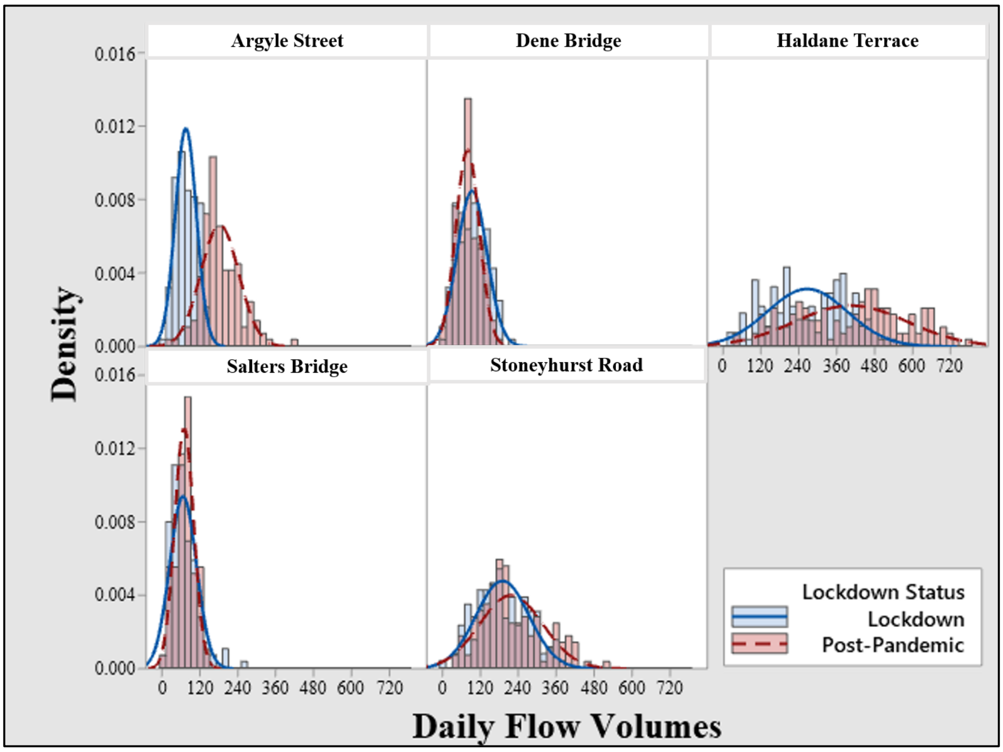

Figure 6.13. Histogram of Cycling Daily Total Flows by Site

The distributions show that Argyle Street and Haldane Terrace have seen large increases in pedestrian flows, whilst they have decreased slightly post-pandemic at the other three. Additionally, histograms suggest that the daily flow counts at the five sites are normally distributed both during lockdown and post-pandemic. With regards to cycling, all but the Dene Bridge site on Castles Farm Road witnessed increases. Similar to the pedestrians, the two sites closest to the City Centre, Haldane Terrace and Argyle Street saw the greatest increases. Daily flow volumes at Haldane Terrace and to a lesser extent Stoneyhurst Road displays a bimodal distribution, with the other sites featuring normal distributions.

Average daily flows for pedestrians and cycling for each of the 23 lockdown weeks are compared with the corresponding post-pandemic week the year after. The results of the for each site are presented in Table 8.

Table 8. Change in mean flows at each site and mode.

Pedestrians					
Site	Change in Mean	StDev	SE Mean	±95% CI	
				Lower	Upper
Argyle Street	1129	484	101	919	1338
Haldane Terrace	618.6	468.6	97.7	416.0	821.2
Dene Bridge	-182.4	85.1	17.7	-219.2	-145.6
Stoneyhurst Road	-317.0	212.8	44.4	-409.0	-225.0
Salters Bridge	-177.4	169.2	35.3	-250.5	-104.2
Cycling					
Site	Change in Mean	StDev	SE Mean	±95% CI	
				Lower	Upper
Argyle Street	106.35	38.27	7.98	89.81	122.90
Haldane Terrace	135.6	112.9	23.5	86.8	184.5
Dene Bridge	-13.76	34.61	7.22	-28.72	1.21
Stoneyhurst Road	18.8	79.5	16.6	-15.5	53.2
Salters Bridge	1.27	39.36	8.21	-15.75	18.28

The results show that whilst overall there was an increase in pedestrians in the post-pandemic period, this was mainly at two sites; Argyle Street and Haldane Terrace, with the other three sites witnessing a reduction in pedestrians. All results being statistically significant with better than 95% confidence.

With regards to the cycling, all but Dene Bridge on Castles Farm Road see increases in the mean. The potential causes for these features were explored in the next section using cluster analysis of the diurnal flow profiles.

6.5 Determining the Number of Clusters

Consistent with Study 1, the total within-cluster sum of squared distances from the centroid was plotted against the number of clusters increasing incrementally to assist with the selection process, as shown in Figures 6.14 (pedestrians) and 6.15 (cycling).

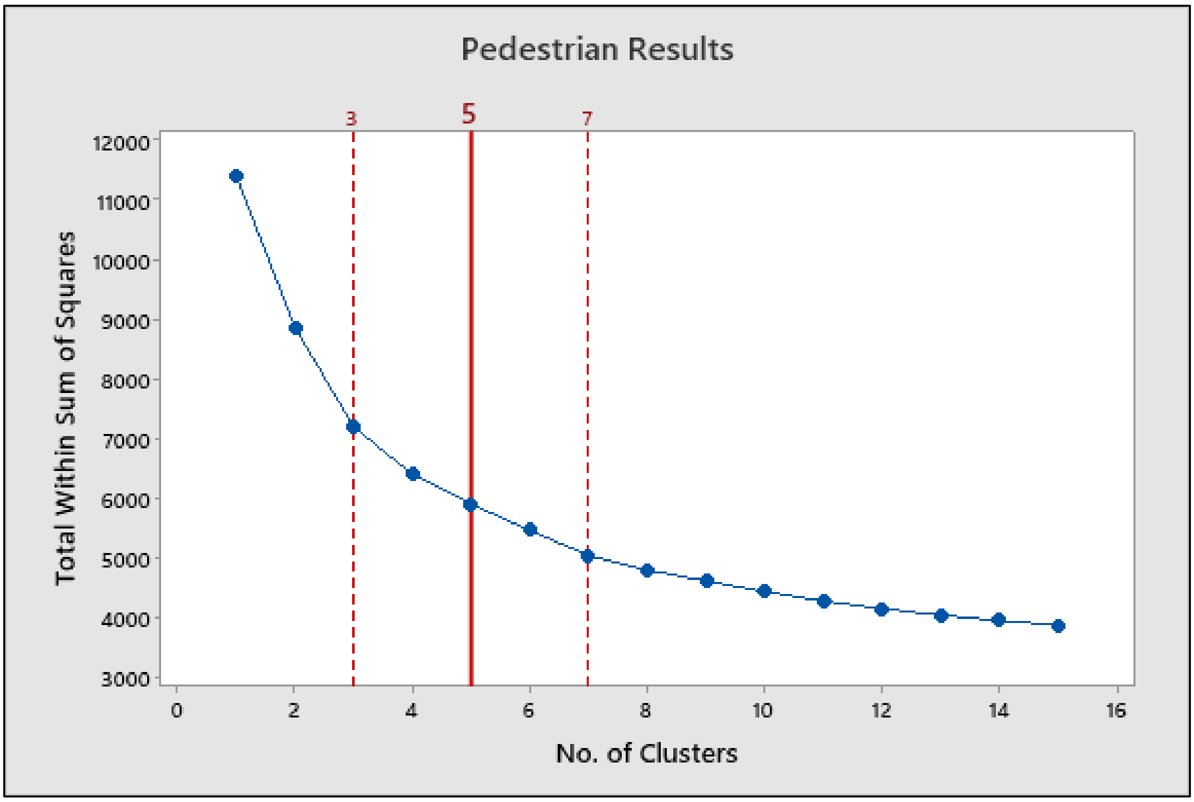

Figure 6.14 Identifying the Elbow for Pedestrian Clustering

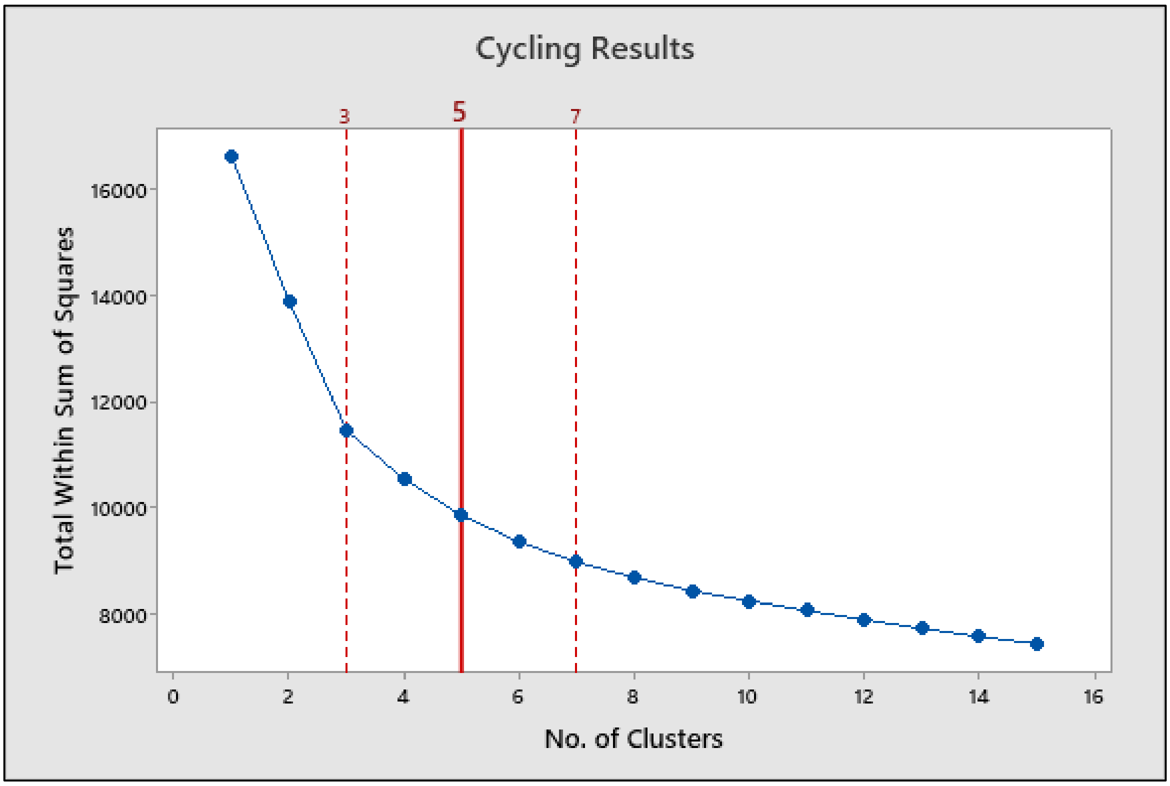

Figure 6.15 Identifying the Elbow for Cycling Clustering

The results show that the “elbow” within the scree plots is not immediately obvious for these data sets but suggests that for both the pedestrian and cycling data sets the optimal number of clusters lies between three and seven. The agglomeration coefficient, determined by the sum of squares of the Euclidean distance measure, is generally smaller within the pedestrian data compared with cycling, suggesting the flows are more similar overall. With reference to Figures 6.14 and 6.15 when moving from a one-cluster solution to two, the dissimilarity within the groups decreases more than at any other stage. Moving from two to three clusters sees another substantial reduction in dissimilarity between clusters, but for each additional cluster after three the rate at which the total within sum of squares declines decrease as the most disparate of diurnal flows have already been separated. After seven clusters, the reduction in dissimilarity begins to level off in both the pedestrian and cycling dataset.

Therefore, the hierarchical cluster analysis was run systematically, specifying a cluster solution for three up to seven clusters and outputting the results. Whilst the elbow technique and within sum of square totals assist in identifying the range of the optimal number of clusters, ultimately the decision is subjective. Whilst it is not required that they are the same, in this case, the optimal number of clusters for both pedestrian and cyclist was found to be five. This was because up to five clusters, each daily flow profile was substantially different from one another (see Figures 6.18 and 6.24). However, when a sixth cluster was introduced, there was no noticeable difference in the shape of the average diurnal flow profiles between two of the separated clusters to add to the discussion of the results. The results of the cluster analysis of pedestrian flows are detailed in the next section.

6.6 Cluster Analysis of Pedestrian Flows

As described in Chapter 3, the hierarchical cluster analysis is a bottom-up agglomeration approach, starting with each flow profile as an individual cluster, which can be seen at the bottom of the dendrogram in Figure 6.16. The agglomeration progresses as the dendrogram increases in height, until there is just one cluster, i.e., the entire dataset. The dendrogram labels and colour coordinates each group formed at the point of a five-cluster solution, as was decided in the previous section. It can be seen the clusters 4 (C4 Ped) and 5 (C5 Ped) merge first indicating that they are the most ` similar, followed by 1 (C1 Ped) and 2 (C2 Ped). Cluster 3 (C3 Ped) then merges with C4 Ped and C5 Ped, suggesting it is more similar in shape to these profiles rather than C1 Ped and C2 Ped. Exploration of the flow profiles of each cluster later on in this section will assist in the understanding of the process.

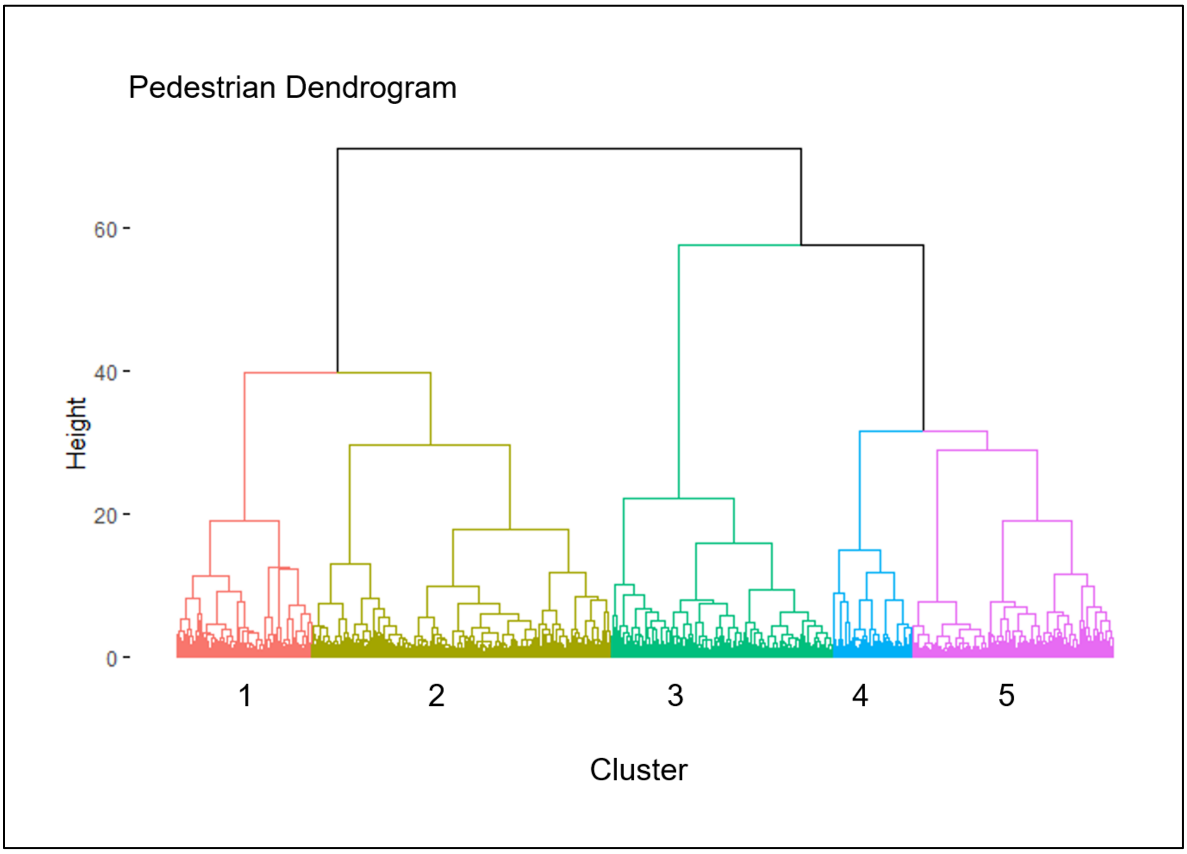

Figure 6.16. Dendrogram of Pedestrian Diurnal Flow Profiles

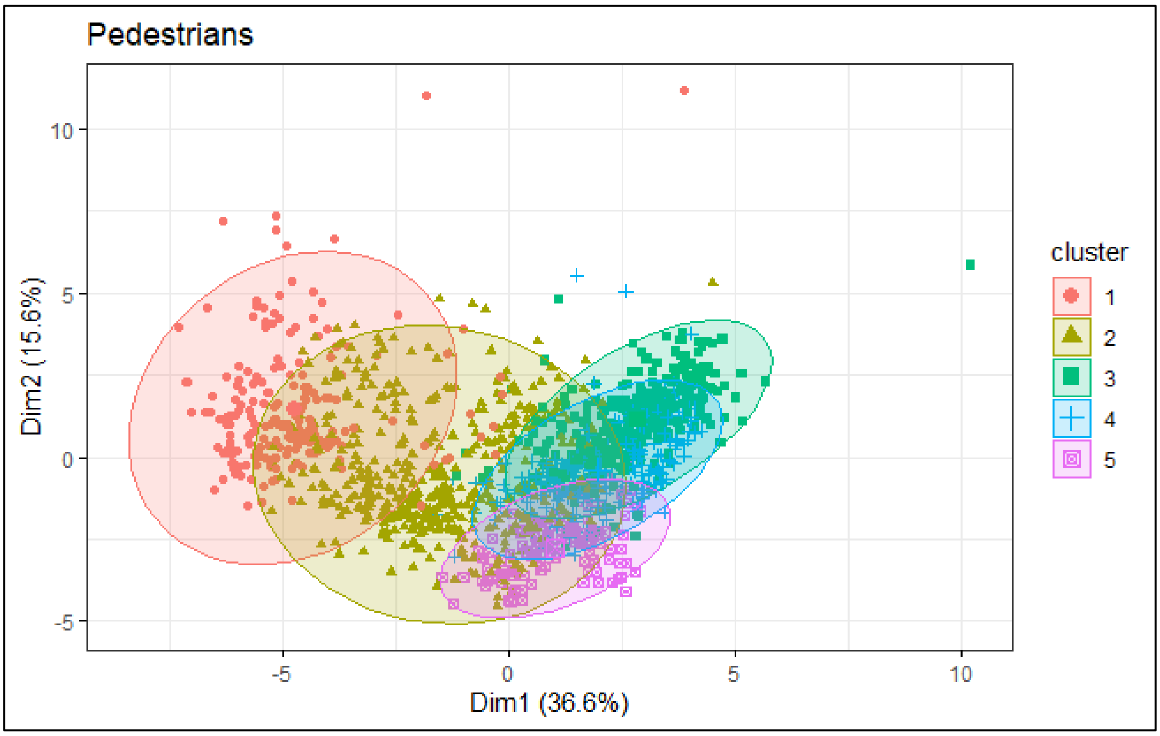

Figure 6.17. Five Cluster Solution PCA Plot for Pedestrian Flows

In addition to the dendrogram, principal components analysis (PCA) was used to visualise the clustering of the results. PCA was applied to the standardised 24-hour counts to create new variables, uncorrelated with one another, which account for decreasing proportions of the total variance of the original data. PCA therefore provides a means of projecting the 24-hour counts into a lower dimensional space. Whilst PCA can be used independently for statistical analysis, it is used in this study as a complementary visual to aid understanding. The results demonstrate similarity with the dendrogram, with C1 sharing most similarity with C2 whereas C3, C4, and C5 group together separated on the opposite side of the scatter plot.

Table 9. Summary of Pedestrian Cluster Results

Value	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Defining Shape	Evening Peak	Late Afternoon Peak	Day Plateau	Sharp AM - PM Peak	Soft AM - PM Peak
Total No. of Daily Counts % of All Counts (nearest 1%)	204 14%	453 32%	336 24%	304 21%	121 9%
Mean Av. Daily Flow Vol.	2,196	1,858	565	734	623
Time Period					
Lockdown (14 Oct '20 – 7 Mar '21)	47%	54%	57%	42%	29%
Post-Pandemic (14 Oct '21 – 7 Mar '22)	53%	46%	43%	58%	71%
TOTAL	100%	100%	100%	100%	100%
Site Location					
Argyle Street	93%	20%	1%	1%	0%
Haldane Terrace	0%	56%	7%	1%	0%
Dene Road	1%	6%	26%	24%	80%
Stoneyhurst Road	1%	9%	24%	47%	6%
Salters Bridge	5%	9%	42%	27%	14%
TOTAL	100%	100%	100%	100%	100%

In order to interpret each of the clusters, the average diurnal flow profiles were plotted using the mean average standardised flow by hour for each cluster, see Figures 6.18 and 6.19. The flow profiles seem to validate the emerging patterns within Figure 6.16 and 6.17, with C4 (Ped Sharp AM – PM Peak) and C5 (Ped Soft AM – PM Peak) being the most similar to one another and the only profiles with peaks at both morning and evening, representing typical commuter-shaped profiles. Therefore, it is logical that these two are the first to cluster together in the agglomeration process. C1 Ped Evening Peak and C2 Ped Late Afternoon Peak are the next to join, and unlike C4 Ped Sharp AM – PM Peak and C5 Ped Soft AM – PM Peak, they do not possess a morning peak, experiencing a gradual increase throughout the day before peaking in the evening at 17:00h – 18:00h. Hourly flows for both C1 Ped Evening Peak and C2 Ped Late Afternoon Peak gradually decline after 18:00h throughout the evening, but not as sharply as the other three clusters. This is perhaps why C3 Ped Day Plateau, which although not featuring a morning peak, clusters with C4 Ped Sharp AM – PM Peak and C5 Ped Soft AM – PM Peak earlier on in the agglomeration stage.

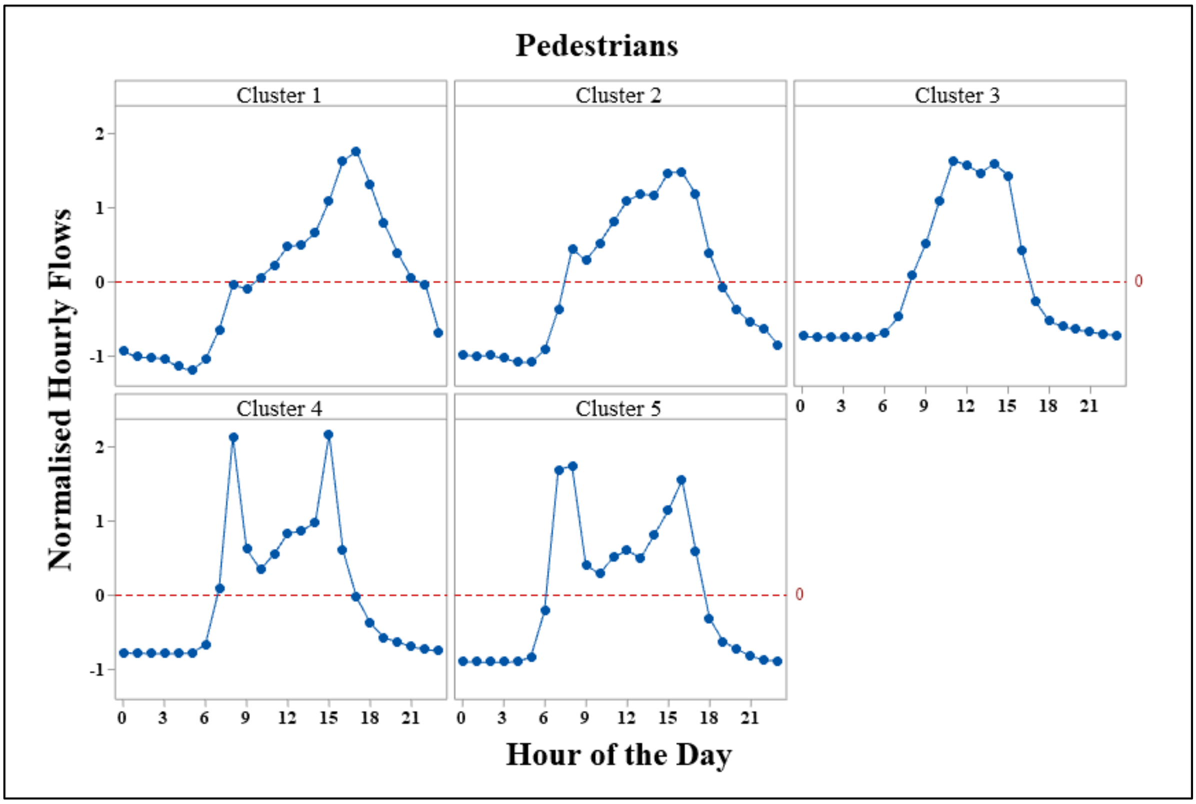

Figure 6.18. Overview of pedestrian cluster profiles individually

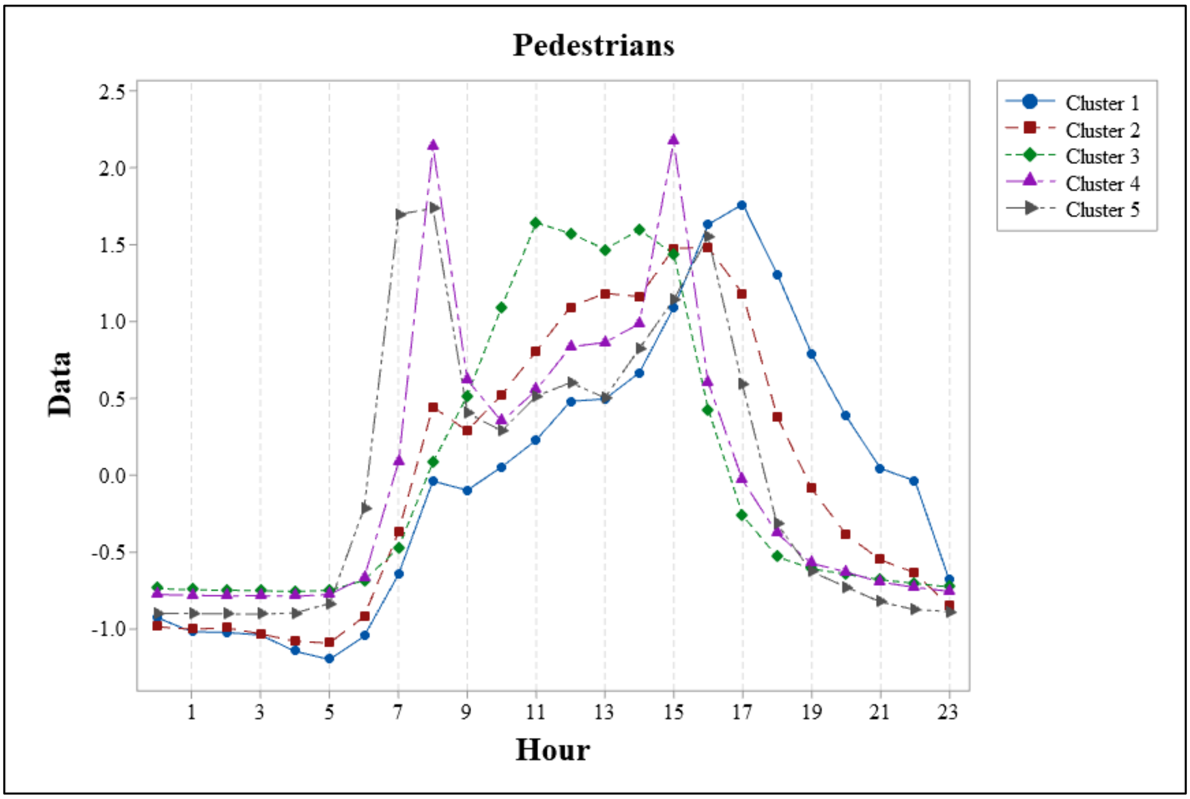

Figure 6.19. Comparison of pedestrian flow profiles

When comparing C4 Ped Sharp AM – PM Peak and C5 Ped Soft AM – PM Peak , one key difference is an element of peak-spreading occurring in the morning within C5 Ped Soft AM – PM Peak (07:00h – 09:00h), and the afternoon peak (16:00h – 17:00h) is not as pronounced as C4 Ped Sharp AM – PM Peak (15:00h -16:00h). The pie charts within Figure 6.20 are a breakdown of each cluster according to lockdown conditions. It can be seen that in the post-pandemic era, a higher proportion of flows are categorised within C5 Ped Soft AM – PM Peak. This could be reflective of the adoption of flexible working, whilst commuters are returning, they are not as restricted to the more regimented commuting periods seen in C4 Ped Sharp AM – PM Peak, which whilst also witnessing an increase in the post-pandemic era, it is not as apparent as C5 Ped Soft AM – PM Peak.

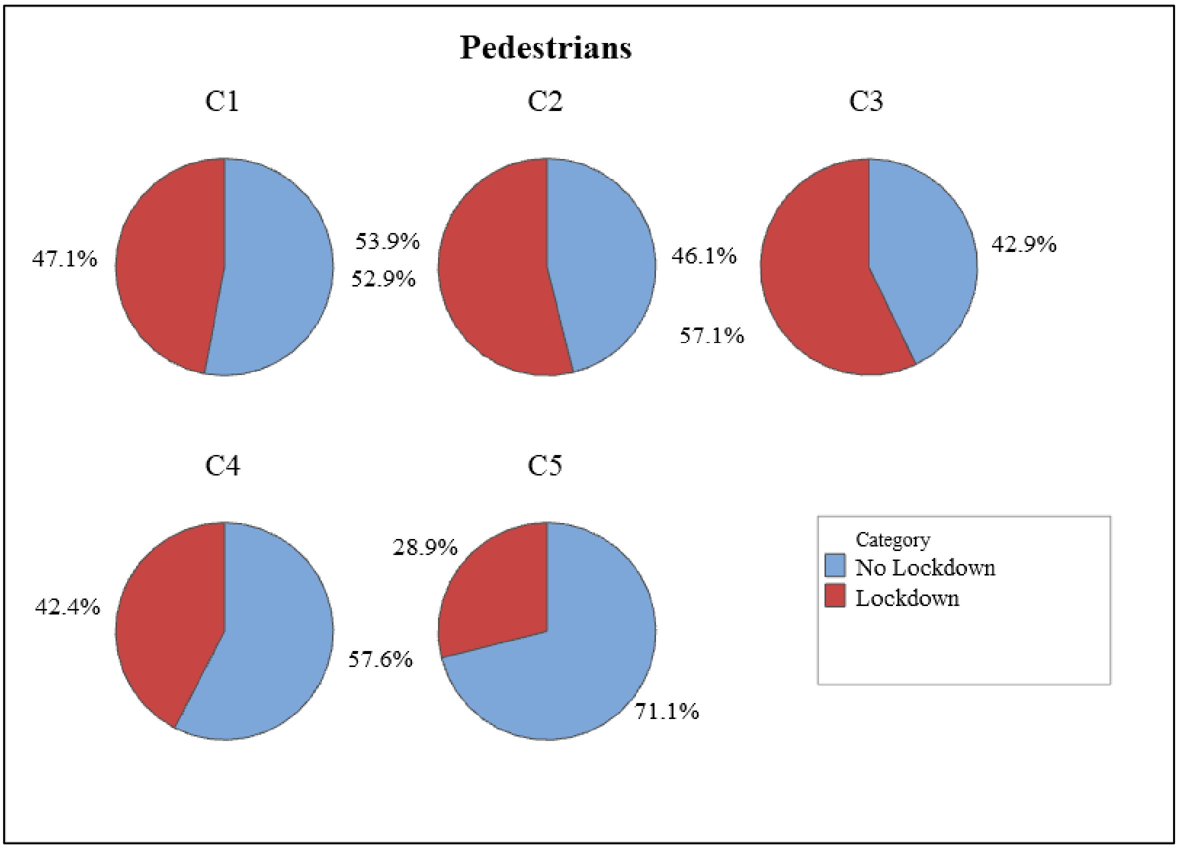

Figure 6.20. Pie Chart showing split of clusters according to lockdown status for pedestrians

As previously mentioned, C4 Ped Sharp AM – PM Peak and C5 represent commute-shaped flows and Figure 6.20 suggests they have returned under the ‘No Lockdown’ conditions of the Post-Pandemic, contributing to 57.6% and 71.1% of the shares, respectively. C1 Ped Evening Peak, C2 Ped Late Afternoon Peak and C3 Ped Day Plateau are more prevalent in the Lockdown era with 52.9%, 53.9% and 57.1% of the share of each cluster, respectively. Their defining flow profiles reflect a lack of the typical morning and evening spike associated with commuter flows.

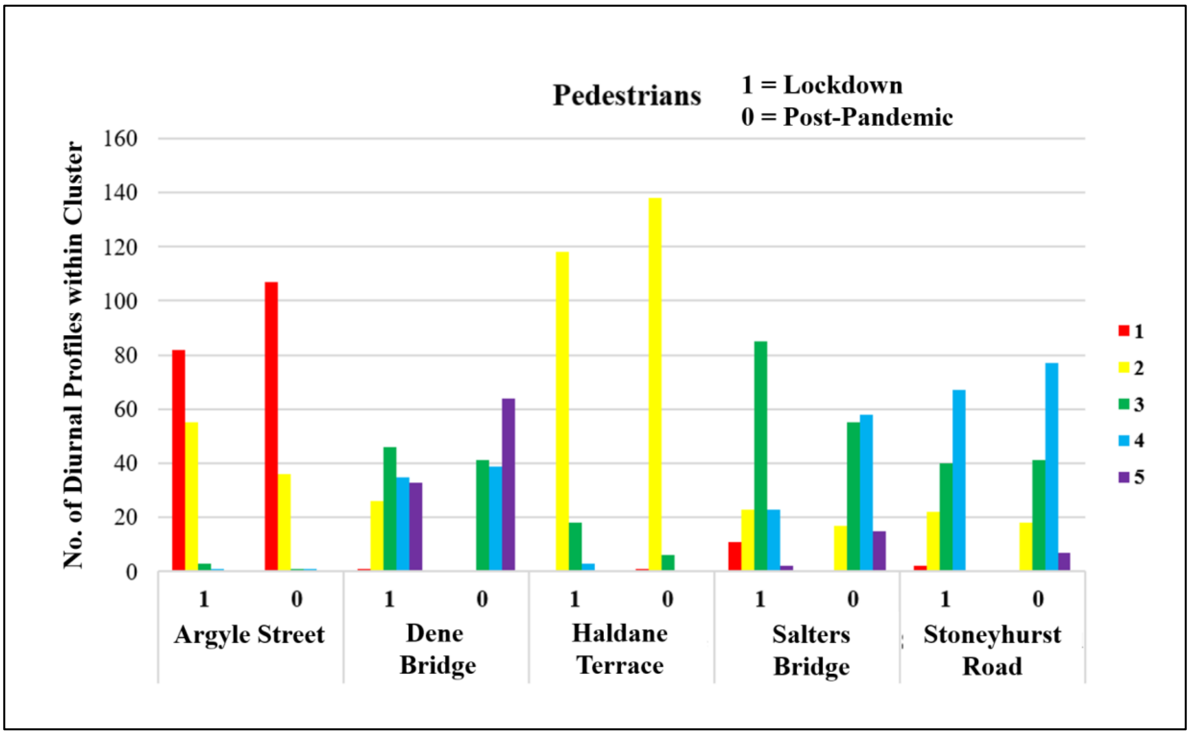

Figure 6.21. Pedestrian cluster membership broken down by lockdown status and site.

Figure 6.21 and Table 10 below disaggregates cluster memberships according by site location and lockdown status, with "1" representing lockdown and "0" representing the post-pandemic period. It can be seen that the composition of cluster membership varies across the five sites. A common pattern at Dene Bridge, Salters Bridge and Stoneyhurst Road Bridge is the transition from non-commuting profiles (C1 Ped Evening Peak, C2 Ped Late Afternoon Peak, C3 Ped Day Plateau) during lockdown to commuter profiles (C4 Ped Sharp AM – PM Peak, C5 Ped Soft AM – PM Peak) in the post-pandemic era. This does not appear to occur at the other two sites, Argyle Street and Haldane Terrace, where C1 Ped Evening Peak and C2 Ped Late Afternoon Peak are the dominant flow profile during lockdown and become even more prevalent in the post-pandemic era. At sites where C1 Ped Evening Peak and C2 Ped Late Afternoon Peak increased, so did the total volumes of pedestrians, whereas the sites where these clusters decreased also saw a decrease in total pedestrian volumes. The following paragraphs discuss each site in turn, inferring trips in the process. As found in Study 1, without qualitative data such as that collected through a questionnaire, the specific trip purposes cannot be known.

Table 10. Lockdown and Post-Pandemic Pedestrian Cluster Membership by Site

Site	Cluster 1 Evening Peak	Cluster 2 Late Afternoon Peak	Cluster 3 Day Plateau	Cluster 4 Sharp AM - PM Peak	Cluster 5 Slight AM - PM Peak	Total
Lockdown						
Argyle Street	58%	39%	2%	1%	0%	100%
Dene Bridge	1%	18%	33%	25%	23%	100%
Haldane Terrace	0%	84%	13%	3%	0%	100%
Salters Bridge	7%	16%	60%	16%	1%	100%
Stoneyhurst Road	2%	17%	31%	51%	0%	100%
Post-Pandemic						
Argyle Street	74%	25%	<1%	<1%	0%	100%
Dene Bridge	0%	0%	29%	27%	44%	100%
Haldane Terrace	1%	95%	4%	0%	0%	100%
Salters Bridge	0%	12%	38%	40%	10%	100%
Stoneyhurst Road	0%	13%	29%	53%	5%	100%

During the Pandemic at Argyle Street Bridge, the diurnal flow profiles are almost entirely either C1 Ped Evening Peak (58%), the evening peak, or C2 (39%), the late afternoon peak. In the Post-Pandemic it appears that there is a partial shift towards flow profiles with later peaks, with C1 Ped Evening Peak up 16 percentage points to 74% and C2 Ped Late Afternoon Peak down 14 percentage points to 25%. With Argyle Street being closest to the restaurants and bars of the Quayside, Ouseburn and the City Centre, this is understandable as these services begin to reopen people visit them in the evenings. This would not explain why Cluster 1 was the most prominent of flow profiles during lockdown conditions. It could be that due to its central location and student population, grocery shopping was taking place in the evening, which due to these factors is likely to be predominantly on foot, whilst locations such as Dene Bridge and Salters Bridge are not located near grocery stores. Argyle Street is near the Quayside, therefore it could also be that this is the time people chose to go for a walk after work or studying as one of the few recreational activities permitted during the lockdown. Being paved and well-let the Quayside is a popular choice for a walk even on winter evenings that make up the majority of the study period.

On Haldane Terrace, the Late Afternoon Peak profile of C2 is the dominant profile over the lockdown, with 84% of the total flow profiles, rising to 95% in the post-pandemic, whilst the Mid-Day Plateau profile dropped from 13% during lockdown to 4% of the total in the Post-Pandemic. In Study 1, the prevalence of mid-day flows increased during the lockdown, and gradually decreased as services began to reopen, this is a continuation of that trend at this particular site as services begin to reopen. As explained in Section 6.1.2, this site shares similarities in land use and demographics with Argyle Street which may contribute to both the similar increases in walking and cycling after the pandemic but also the similar diurnal flow profiles with peaks later-on in the day which are prevalent at each site.

Prior to the cluster analysis, it was expected that Dene Bridge and Salters Bridge may share similar results with each other, as they are located in the more suburban surroundings of Gosforth and directly placed next to recreational trails and parks. To some extent they are similar, they possess a wider range of diurnal flow profiles than Argyle Street and Haldane Terrace bridges. The lockdown period at Dene Bridge has the most diverse results in terms of diurnal flow profiles, with C2 Ped Late Afternoon Peak (18%), C3 Ped Day Plateau (33%), C4 Ped Sharp AM – PM Peak (25%) and C5 Ped Soft AM – PM Peak (23%) all being represented, providing a mix of traditional AM – PM commute shapes in C4 Ped Sharp AM – PM Peak and C5, shapes with afternoon peaks (C2) and shapes with Mid-Day flows (C3). The major shift at Dene Bridge in the Post-Pandemic period is the disappearance of C2 Ped Late Afternoon Peak and increase in C5 Ped Soft AM – PM Peak to 44% of the total diurnal flow profiles. This could be explained by a shift from recreational walks in and around the nearby Jesmond Dene as a lockdown activity to a return to work at nearby employment facilities such as the Freeman Hospital and HMRC offices.

At Salters Bridge the Mid-Day Plateau profile of C3, that can be inferred to be a result of more recreational trips, formed the majority of diurnal profiles (60%) during lockdown. This reduced to 38% of the total in the post-pandemic. Conversely, the sharp AM-PM peak shape of C4 became the most common profile at this site increased from 16% to 40% once lockdown ended and people could return to work, the largest change in diurnal flow profiles at Salters Bridge. It is thought that given the quiet surroundings and nearby footpaths paths to the site, it would have been an attractive place to walk recreationally during lockdown. Taking a wider view of the area and its transport links, the bridge links Gosforth Industrial Estate to the west with Longbenton residential estate and the bus route along the A189 Primary Distributor Road to the east, which would provide the traditional commuter-shaped profile of C4 Ped Sharp AM – PM Peak once the lockdown was lifted. There was also an increase in the softer AM-PM peak of C5 from 1% during lockdown to 10% of the total in the post-pandemic to provide further evidence of the shift to commuter-shape flows after lockdown.

Finally, the proportions of clusters at Stoneyhurst Road remained fairly consistent across lockdown and the post-pandemic, with a slight shift towards more commuter-shaped profiles, C4 Ped Sharp AM – PM Peak increasing just 2 percentage points from 51% to 53% and C5 Ped Soft AM – PM Peak, the softer peaks with more AM peak spreading, representing 5% of the post-pandemic flows where during the lockdown it was 0%. Therefore, proportionately C5 Ped Soft AM – PM Peak has increased in the post-pandemic much more than C4 Ped Sharp AM – PM Peak, which could be due to more flexible working conditions becoming more normal when people returned to work after the pandemic. The fact that there has been less change in the diurnal flow profiles at Stoneyhurst Road could be a result of it being located within a residential area with a more diverse mix of trips starting and ending surrounding it. The results of the cluster analysis of cyclist flows are detailed in the next section.

6.7 Cluster Analysis of Cyclist Flows

Similar to the pedestrians, the dendrogram is colour-coordinated based on a five-cluster solution for the cyclist diurnal flows and shown in Figure 6.22. As the agglomeration process proceeds, Cluster 1 (C1 Cyc) and 2 (C2 Cyc) are the first to cluster together, followed by C4 Cyc and C5 Cyc. C3 Cyc joins the already fused C4 Cyc and C5 Cyc pairing in the final step before the entire dataset is fused into one group at the top of the dendrogram.

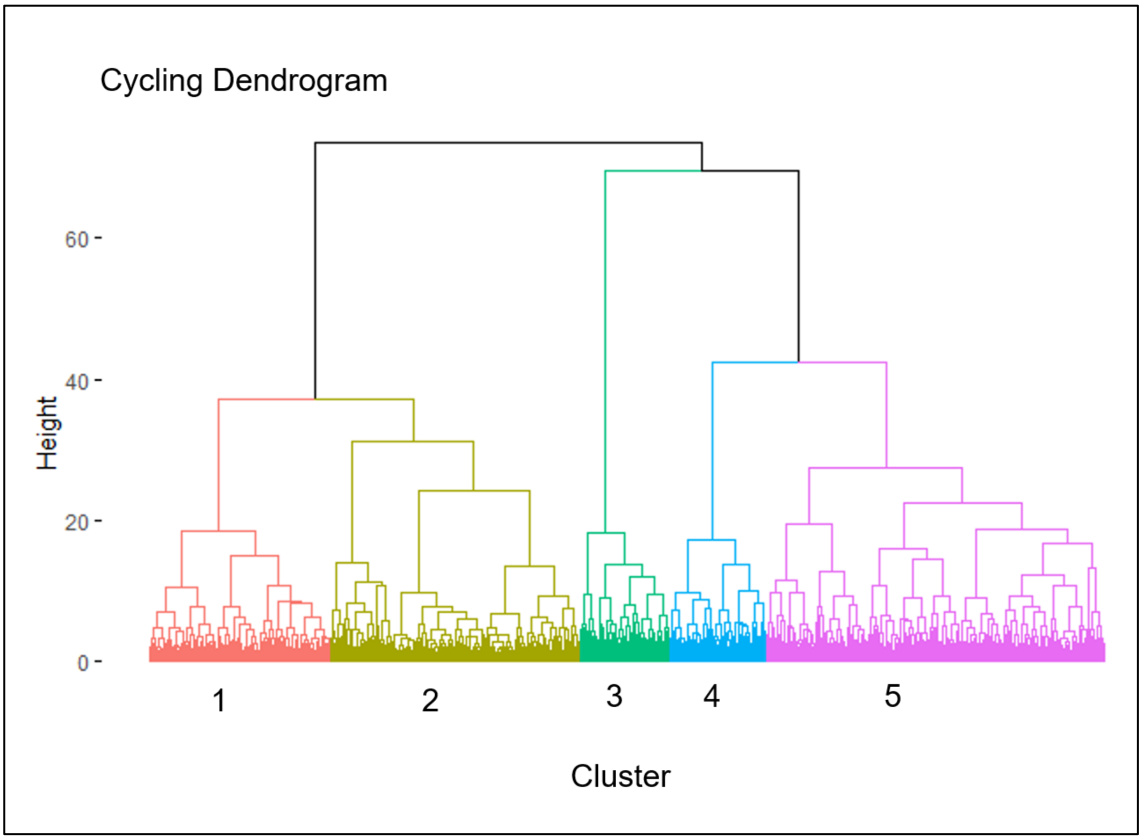

Figure 6.22. Dendrogram visualising Agglomeration Schedule of Cycling Cluster Analysis

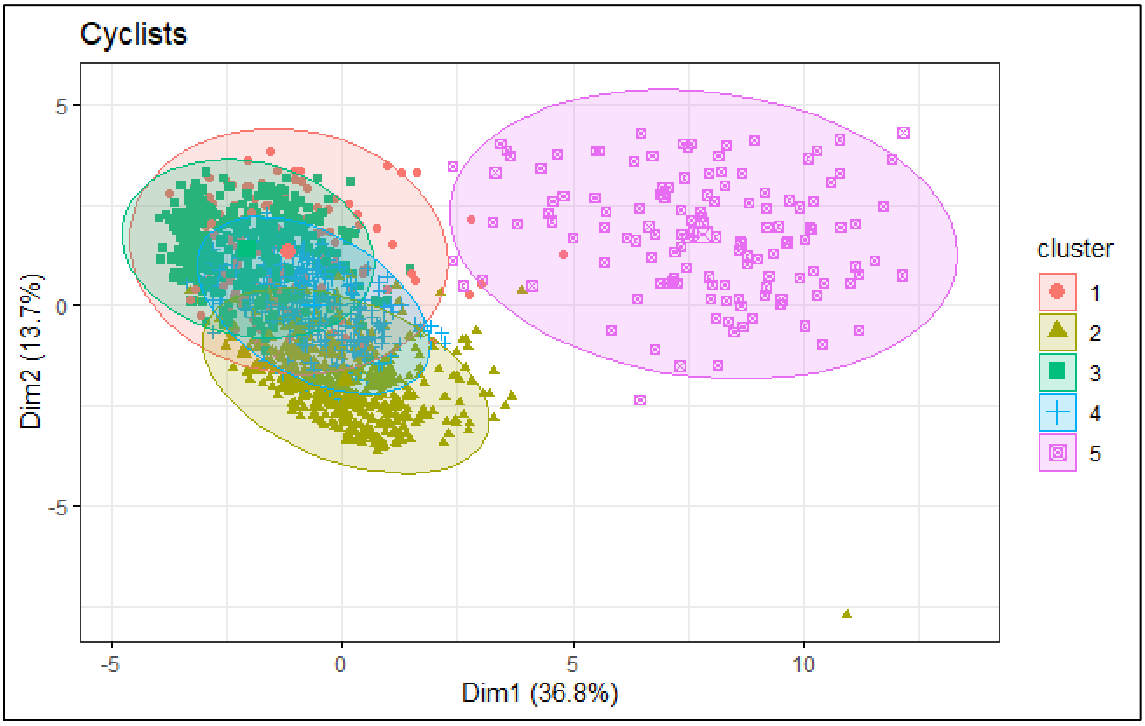

Figure 6.23. Five Cluster Solution Plot for Cyclist Flows

When compared with the pedestrian scatter plot, the cycling profile clusters are less distinguishable from one another, with the exception of C5 which seems notably dissimilar when compared to the other 4 clusters. It should be noted that in this case the first dimension of the principal component analysis explains 36.8% of the variation within the data and the second 13.7%. So, with reference to the PCA plot in Figure 6.23 C5 would be expected to be the last to merge in the agglomeration schedule, rather than C3 – Cyc AM & Spread PM peak, it is only representing half of the variation within the dataset. The diurnal flow profiles in Figures 6.24 and 6.25 offer some insight into the reasoning for this as explained later in this section.

Table 11. Summary of Cycling Cluster Results

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Defining Shape	Mid-day peak with gradual evening fall	Mid-day peak with sharp evening fall	AM & Spread PM peak	Sharp AM peak & PM peak	High evening flows
Total No. of Daily Counts	142	502	369	269	134
% of All Counts (nearest 1%)	10%	35%	26%	19%	10%
Mean Av. Daily Flow Vol.	167	91	275	142	183
Time Period					
Lockdown (14 Oct ‘20 – 7 Mar ‘21)	68%	64%	46%	41%	0%
Post-Pandemic (14 Oct ‘21 – 7 Mar ‘22)	32%	36%	54%	59%	100%
TOTAL	100%	100%	100%	100%	100%
Site Location					
Argyle Street	49%	14%	3%	1%	100%
Haldane Terrace	44%	10%	41%	7%	0%
Castles Farm Road	2%	20%	20%	40%	0%
Stoneyhurst Road	2%	22%	25%	25%	0%
Salters Bridge	3%	34%	11%	28%	0%
TOTAL	100%	100%	100%	100%	100%

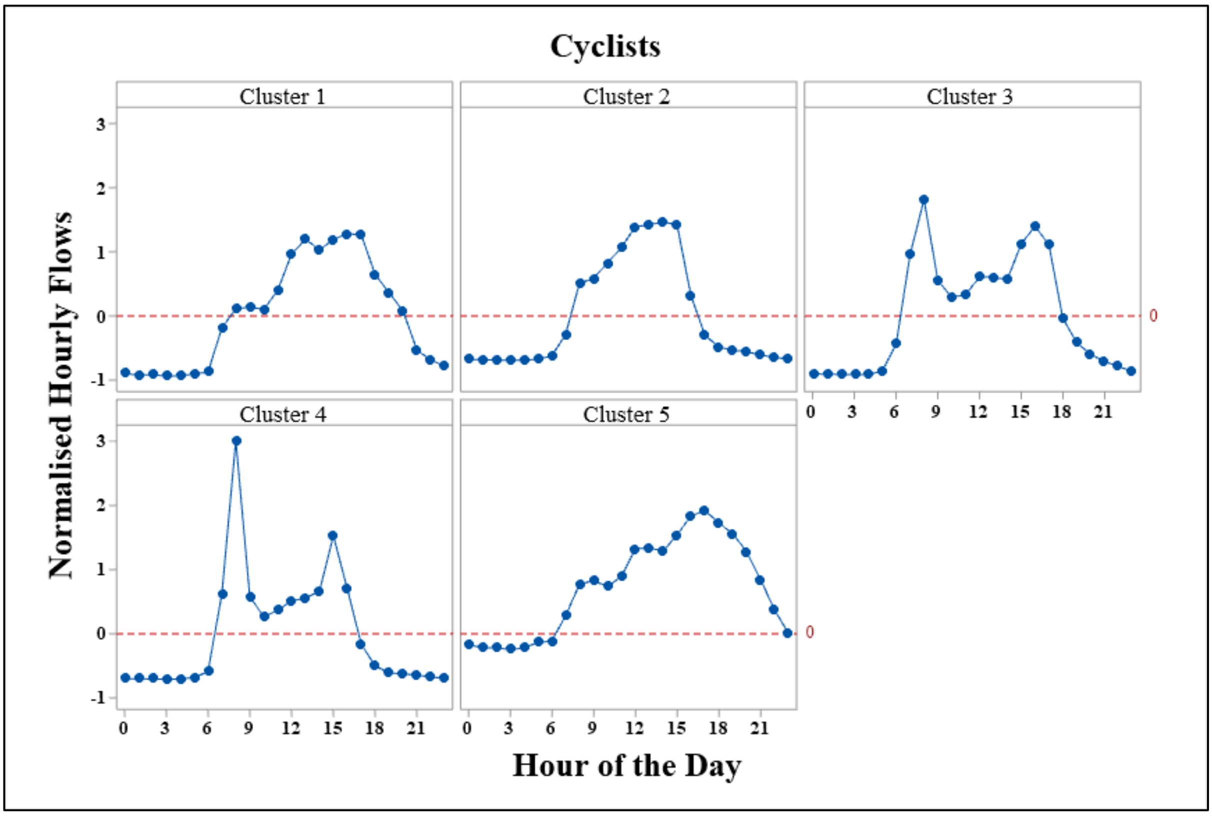

Figure 6.24. Overview of Cycling Cluster Profiles Individually

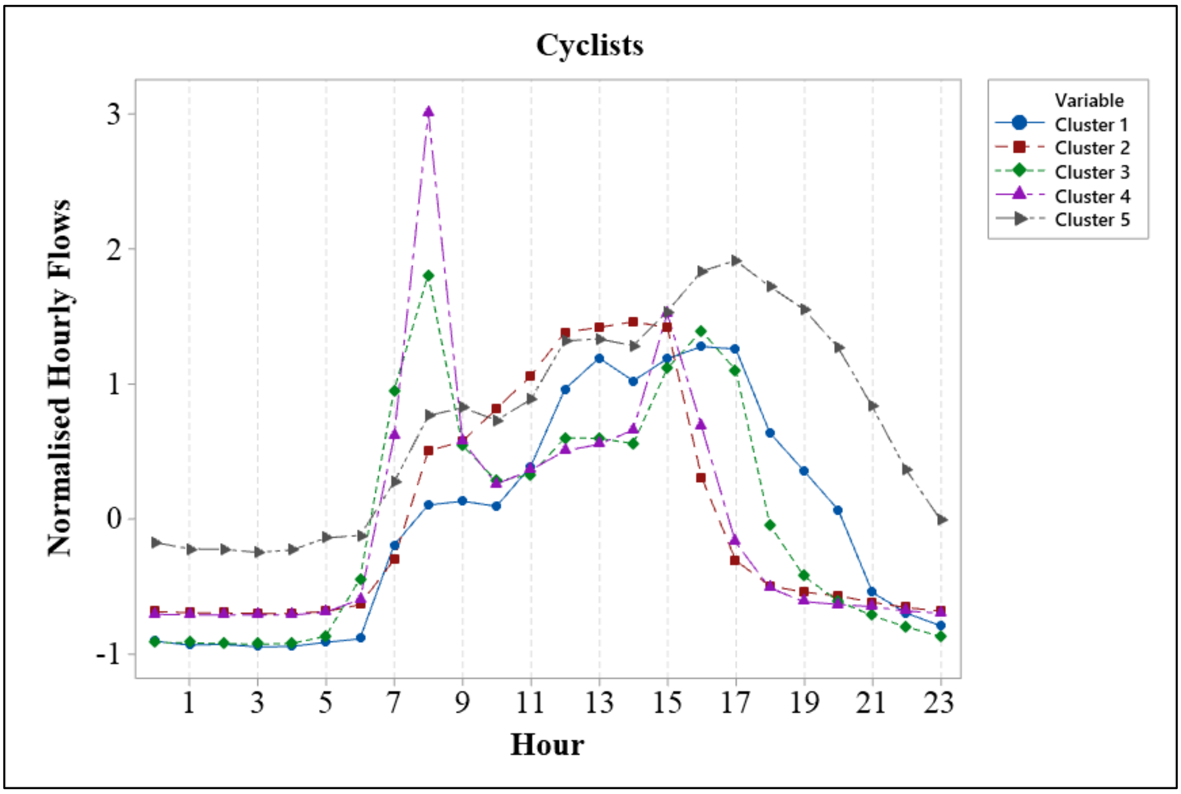

Figure 6.25. Comparison of cycling flow profiles

The average flow profiles of C1 - 'Cyc Mid-day peak with grad. eve. fall' and C2 appear similar, and it is understandable that they are the two that cluster together in the next step of the agglomeration schedule shown in the dendrogram in Figure 6.22. It becomes apparent that C5 Cyc - High evening flows differ in two distinctive ways to the other clusters. The standardised flows between the hours 00:00h and 06:00h in C5 Cyc - High evening flows are higher than the other groups, and flows peak in the evening (17:00h – 18:00h), but unlike a commuter profile they remain high either side demonstrating a peak spreading profile. With reference to Table 11, C5 Cyc - High evening flows on average possesses the lowest average daily flows in terms of volume, which alongside the spread of flows across a wider part of the day mean that the night flows are relatively closer to the day flows and therefore have higher standardised values than the other sites. C3 – Cyc AM & Spread PM peak and C4 - Cyc Sharp AM peak & PM peak are the two clusters that resemble commuter shaped profiles, both possessing morning peaks at 08:00h – 09:00h with C4 Cyc having the sharpest peaks as the name suggests, particularly in the morning. In the evening, C3 – Cyc AM & Spread PM peak has higher normalised flows between 15:00h-18:00h, peaking at 16:00h – 17:00h, whilst C4 – Cyc Sharp AM peak & PM peak peaks slightly earlier and more sharply at 15:00h – 16:00h.

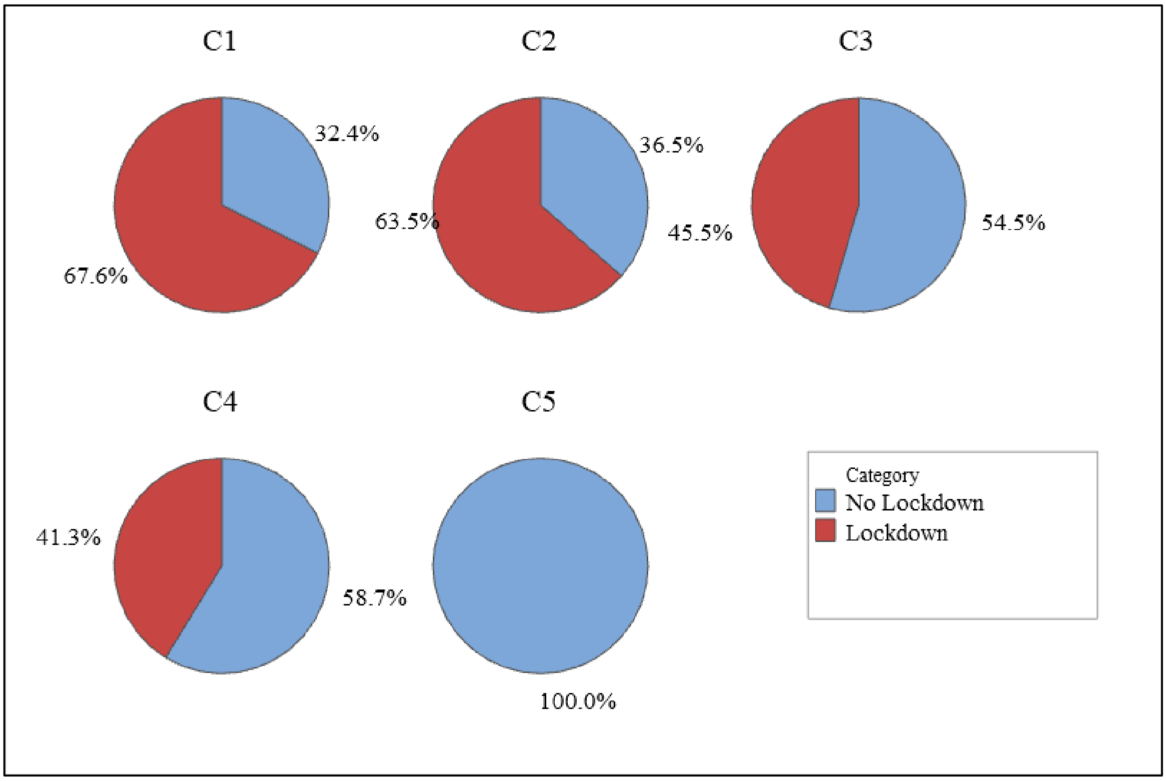

Figure 6.26. Pie Chart showing split of clusters according to lockdown status for cyclists.

Similar to the pedestrians, the pie charts in Figure 6.26 show a contrast in diurnal flow profiles between the lockdown period and no lockdown in the post-pandemic period. The morning and evening peak flows of C3 – Cyc AM & Spread PM peak and C4 are more prevalent in the post-pandemic era, although perhaps not as much as would be expected when compared to the lockdown, when all but essential workers would be expected to be WFH. Figure 6.27 and Table 12 provides a full breakdown of cluster membership by site.

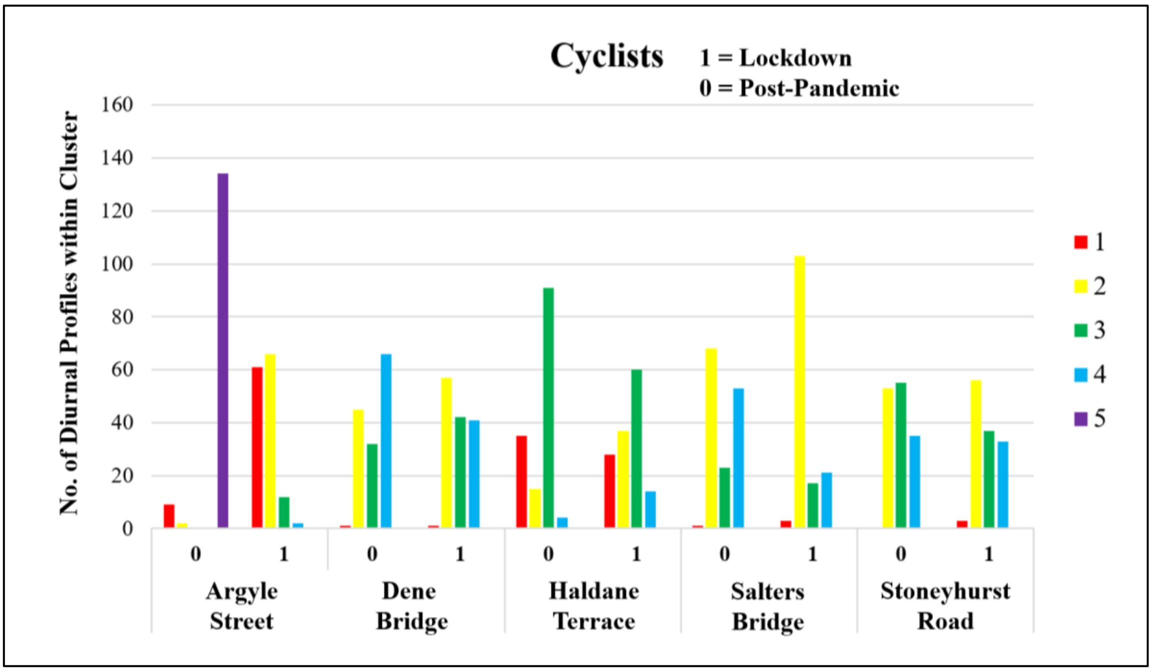

Figure 6.27. Cycling cluster membership broken down by lockdown status and site

Table 12. Cluster Membership by Site for Cycling

Site	C1 Mid-day peak with gradual evening fall	C2 Mid-day peak with sharp evening fall	C3 AM & Spread PM peak	C4 Large AM peak & PM peak	C5 High Evening Flows	Total
Lockdown						
Argyle Street	43%	47%	9%	1%	0%	100%
Dene Bridge	1%	40%	30%	29%	0%	100%
Haldane Terrace	20%	27%	43%	10%	0%	100%
Salters Bridge	2%	71%	12%	15%	0%	100%
Stoneyhurst Road	2%	43%	29%	26%	0%	100%
Post-Pandemic						
Argyle Street	6%	2%	0%	0%	92%	100%
Dene Bridge	1%	31%	22%	46%	0%	100%
Haldane Terrace	24%	10%	63%	3%	0%	100%
Salters Bridge	1%	47%	16%	36%	0%	100%
Stoneyhurst Road	0%	37%	38%	25%	0%	100%

C5 Cyc - High evening flows is a cluster where 100% of the flow profiles in this cluster occurred within the post-pandemic era. Figure 6.27 reveals that not only are these flows only associated with one time-period, but one site in particular, Argyle Street. The defining shape of C5 in Figure 6.24 appears to be one that possesses flows across the day, building gradually up until 17:00h before slowly decreasing as the evening continues. During the lockdown, Argyle Street experiences a wider range of flow profiles, with C2 – ‘Cyc Mid-day sharp eve. fall’ the most common (47%), not far behind is C1 - 'Cyc Mid-day peak with grad. eve. fall’ (43%). Both these clusters feature mid-afternoon peaks.

On the other hand, Haldane Terrace, with similar surroundings to Argyle Terrace experienced a shift to AM-PM commuter shapes after lockdown. As described in Section 6.1.2, Haldane Bridge connects with a popular cycle route into Newcastle City Centre, so it is logical that an AM-PM Peak shape for example C3 – Cyc AM & Spread PM peak after the lockdown is up 20 percentage points from 43% to 63%. Whilst C3 – Cyc AM & Spread PM peak shows evidence of PM Peak spreading, conversely, the other AM-PM peak shape, C4, does not and is down 7 percentage points from 10% to 3% of the total diurnal flows in the post-pandemic.

Moving north away from the City Centre at Dene Bridge on Castles Farm Road the opposite trend emerges, with C4 – Cyc Sharp AM peak & PM peak increasing from 29% to 46% and C3 – Cyc AM & Spread PM peak decreasing from 30% to 22%. However, an overall increase in commuter shaped diurnal profiles shapes after the lockdown remains. This replaces C2 – ‘Cyc Mid-day sharp eve. fall’, which possessing a mid-day peak, drops from 40% to 31%.

The cycling diurnal flow profiles at Stoneyhurst Road Bridge followed a similar pattern to the pedestrian clustering results. The bridge experienced the least dramatic shift in profiles of the sites from the lockdown to the post-pandemic period. Additionally, there was a shift to C3 – Cyc AM & Spread PM peak, the cluster with evidence of the PM-Peak spreading from 29% in the lockdown to 38% of the total in the post-pandemic period. C4 - Cyc Sharp AM peak & PM peak on the other hand witnesses a drop of 1 percentage point from 26% to 25% of the total flows which is not significant.

Salters Bridge is another site where the cycling clustering results follow a similar trend to those of the pedestrian. There is a drop in C2 – 'Cyc Mid-day sharp eve. fall' from 71% in the lockdown to 47% of the total in the post-pandemic, whilst the AM-PM Peak diurnal flow profile of C4 – Cyc Sharp AM peak & PM peak more than doubles from 15% to 36%, both can be attributed to the same reasons as the trends in the pedestrian flows.

C4 - Cyc Sharp AM peak & PM peak is almost entirely present at the Dene Bridge, Stoneyhurst and Salters sites. They also overall increase in number in the post-pandemic period. This could be as a result of more families living in the area, whilst adults can adopt flexible working, they still drop off children at school, producing a spike in the AM peak period. Those in flexible working arrangements then can choose between working from home or heading in to the office, reducing the flows at other times in the day which would emphasise the AM spike further.

6.8 Effect of Student Population on the Results

Sections 6.6 and 6.7 have described the variation of the shifts in diurnal flow profiles of pedestrians and cycling, respectively. Where appropriate, characteristics of both the immediate and wider surroundings of the five sites have provided some context to these results. One of the patterns that emerged is a noticeable split of the five sites into two groups. The two most central sites, Argyle Street and Haldane Terrace, possess more diurnal flow profiles which peak in the evenings when compared to the other three sites for both cycling and pedestrian flows. Additionally, Section 6.2 demonstrated these two sites experience a substantially higher increases in total daily flow volumes in the post-pandemic era for both modes, whereas the other three sites only experience modest changes. Referring back to Section 6.1.2, it is noted that both Argyle Street and Haldane Terrace are located in areas with high student populations. One explanation is that during the lockdown no in-person teaching occurred at Universities and many students would have chosen to move out of Newcastle during lockdown to be with their family back at home. Upon the lifting of lockdown, they returned which resulted in the increased flow volumes, particularly for pedestrians.

To assess this, the prominence of students within the study area was mapped using Geographical Information Systems software QGIS. 2021 Census data was explored to identify how many students resided in each area to confirm there was a noticeable difference. The “Student accommodation by age” dataset was explored, which estimates schoolchildren and full-time student populations of ages five years and over in England according to the type of student accommodation in which they reside. As we are only interested in students in higher education, particularly those that have moved to Newcastle and therefore would have been more likely to return to their family homes during the lockdown era, students aged 18 and who were living in communal establishments owned by the University or privately, or in an all-student household were selected. Data was downloaded from the ONS Census website (ONS, 2023) at Output Area level for the entire North East region and presented as a choropleth map in Figure 6.28.

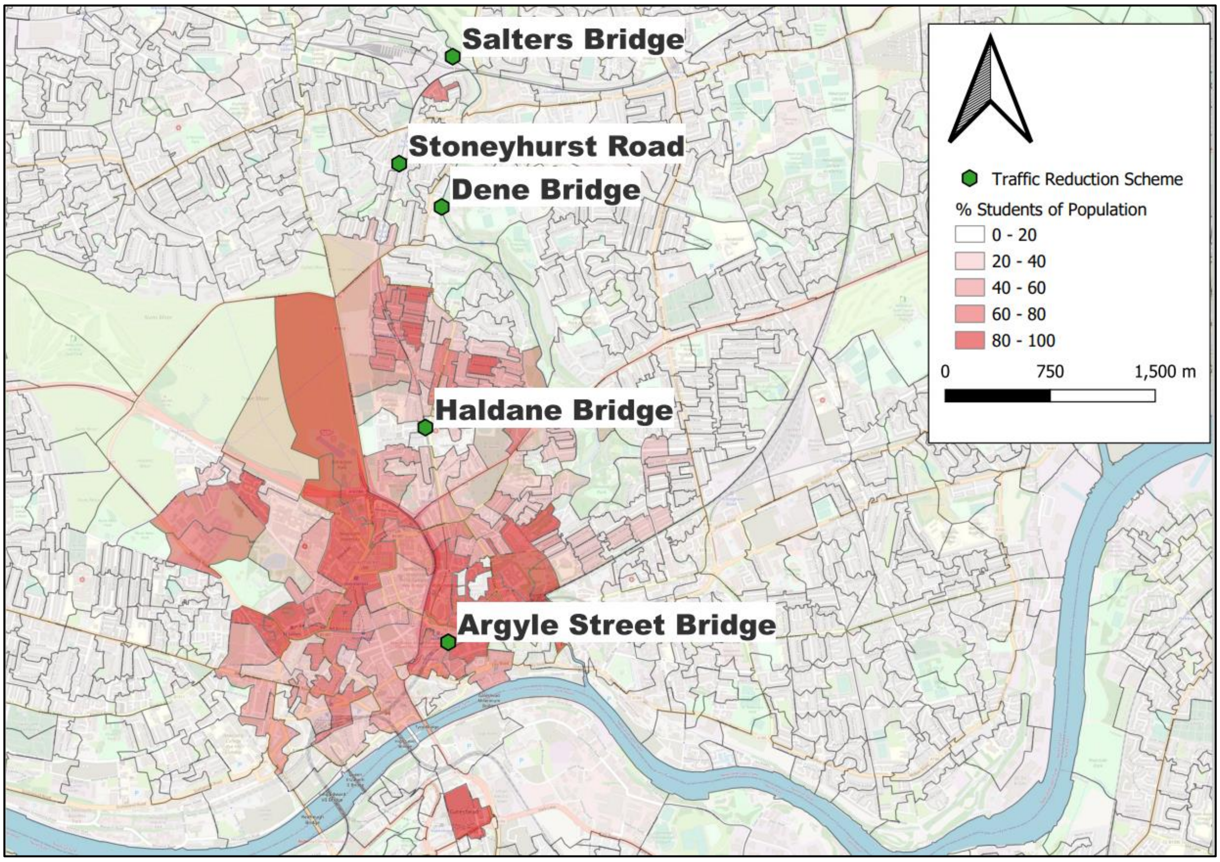

Figure 6.28 Sites in Relation to Student Population

Figure 6.28 shows that the bridges on Argyle Street and Haldane Terrace are surrounded by student populations, many Output Areas containing a population of over 80% students. As to be expected, Stoneyhurst Road, Dene Bridge and Salters Bridge being further out of the city centre are situated in areas of much lower student population. If up to 80% of the population are students, significant numbers of the local population would have been expected to have left the area during the pandemic, returning to their families elsewhere in the country for the lockdown period. To further examine this impact, the daily average flow volumes at each site were plotted for pedestrians (Figure 6.29) and cycling (Figure 6.30) and compared with the term times of Newcastle University across the study period. Each of the dates along the top of Figures 6.29 and 6.30 represents the beginning and end of Newcastle University term time.

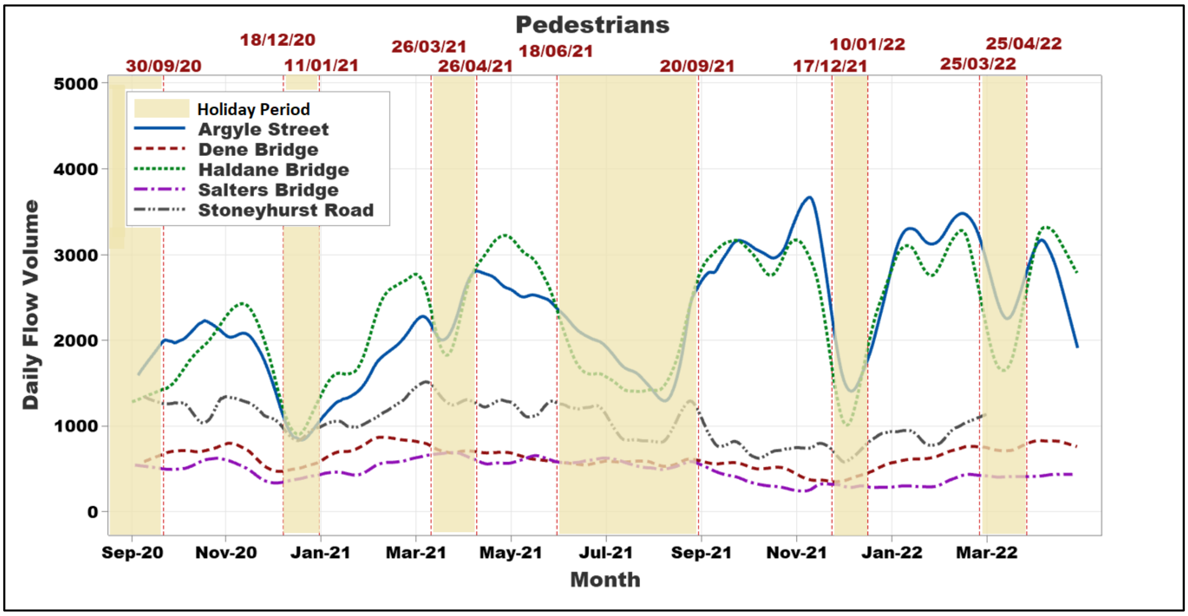

Figure 6.29 University Term and Pedestrian Flows

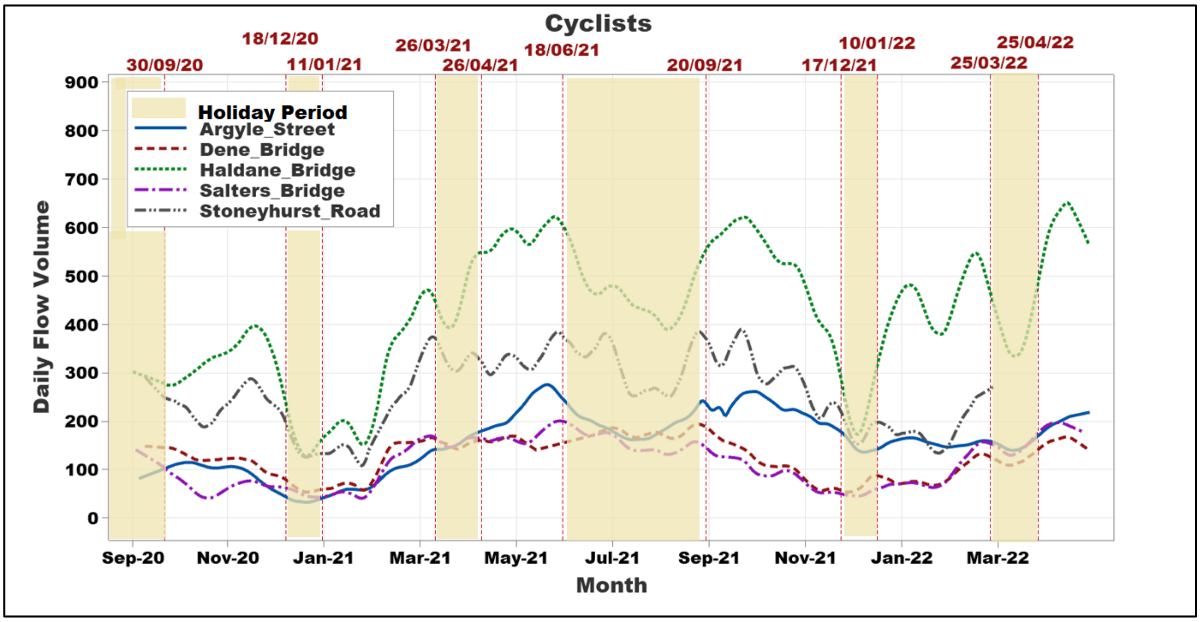

Figure 6.30 University Term and Cyclist Flows

It is evident that the University term times have an effect on the total daily flows of two sites in particular, Haldane Bridge and Argyle Street. This is particularly noticeable in the pedestrian flows and it can be seen that the breaks in term during the 2020/21 academic year are less distinctive than the 2021/22 year, suggesting that the lockdown did affect the flows of active travel at the sites closer to student populations than those that did not. Another observation with respect to the two graphs is that seasonality could affect cycling more than pedestrian flows, with total volumes dipping during the winter months. However, the conclusion drawn from this exploratory study is that the student population could be responsible for the large increases in daily flow volumes of pedestrians up 72% at Argyle Street and 37% at Haldane Terrace. This also highlights a limitation when trying to identify post-pandemic shifts in flow profiles and volumes without the presence of pre-pandemic data and will be discussed further in the next section.

6.9 Discussion

As identified in the literature review prior to the pandemic, LTNs were often met with opposition (Aldred et al., 2019). For this reason, it was considered important to research how they are being used in the post-pandemic era to provide additional information to decision-makers as to whether they remain beneficial after the lockdown-era active travel boom. This proved to be the case as the findings from this chapter were requested by a Senior Transport Planner at Newcastle City Council (NCC) on the 24th June 2022 to input into a report on “the effectiveness of cycling investment” within Newcastle upon Tyne. Similar to the other two studies within this thesis, Study 2 pays particular attention to the changes in the diurnal flow profiles at the sites, complementing NCC’s own analysis of the schemes used in this case study.

Overall, cycling and walking increased across the five former EATF sites. The volumes of pedestrians are substantially higher than the cyclists generally, but it was cycling that proportionately witnessed the greater increase, up 40% in the post-pandemic era compared to lockdown volumes. Breaking down the changes by site, it is clear that two of the five sites, Argyle Street and Haldane Terrace, experienced substantial increases, whereas the other three sites only saw modest growth, stayed largely the same or decreased slightly. Maintaining at least some of the unprecedented levels walking (Nikiforiadis et al., 2022) and cycling (Hong et al., 2020; Burke et al., 2022) that was seen during the lockdown period in the post-pandemic period is a positive step.

In terms of the diurnal flow profiles, both walking and cycling witnessed an increase in commuter-shaped profiles and a decrease of mid-day flows, which are more associated with recreational trips. This suggests that in the post-pandemic study period as people were permitted to travel back into work, they did so using active travel, although the contrast between pandemic and post-pandemic was not as great as perhaps expected. This could be due to working from home arrangements being maintained after restrictions were lifted, as predicted in (Bick et al., 2021; Jain et al., 2022). The pedestrian flows showed signs of peak-spreading, with the diurnal flow profiles with this cluster characteristic (C5 Ped Soft AM – PM Peak), increasing proportionately more in the post-pandemic period than the other commuting cluster without peak-spreading (C4 Ped Sharp AM – PM Peak).

The methodological review demonstrated that there are many ways to cluster diurnal flow profiles, and the optimal method depends on the aim. In this study, the flow profiles clustered relatively freely irrespective of which sites to which they are tied. Consistent with Study 1, it has been demonstrated that by normalising hourly flows, data from more than one site can be analysed at once, with the advantage many clusters spanning all sites over both modes but without compromising identifying specific outcomes associated with particular sites. For example, C5 Cyc - High evening flows in the cycling analysis, and to a lesser extent C1 Ped Evening Peak in the pedestrian analysis, were very much associated with Argyle Street.

One major limitation with this study is that as the MVC were only installed at the same time as the EATF schemes were implemented, therefore there was no pre-pandemic walking and cycling flow data available with which to compare the post-pandemic period. This means that in this case study it was not possible to confirm or reject that walking and cycling volumes have decreased, returned to pre-pandemic levels, or increased. The same applies to the diurnal flow shapes, for example, at Salters Bridge, is the shift from mid-day flow profiles during the lockdown to commuter-shaped post-pandemic a result of the low traffic measures, a post-pandemic new-normal, or simply a return to how it was pre-pandemic? Given that the introduction of Machine Vision cameras for transport planning is only recently becoming widely adopted and the original purpose of these schemes was reactive towards the pandemic, this is understandable. However, one recommendation this chapter makes is that the adoption of a permanent network of cameras would enable historical comparisons of pedestrians and cyclists to be made in the future, in the same way as is possible with counts from inductive loop detectors for motorists and cyclists today from organisations such as TADU.

Also, it should be noted that increasing walking and cycling on these bridges was not the only objective for these schemes. Most of these structures were built long before cars existed and therefore not suitable for heavy flows of motorised traffic, furthermore theses bridges were increasingly used as rat-runs to avoid heavy congestion and therefore steps were taken to prevent their use by through-traffic, creating safer and cleaner environments for the neighbouring residential areas.

Because of the timing of the lockdown, most of the dataset covers the winter months. Newcastle upon Tyne sits at 55 degrees north latitude and the weather during this time is generally cold and windy often with rain. Due to the latitude the winter days are extremely short with the sun setting before 16:00h. In the depths of winter, icy conditions are common. Seasonality is an important consideration when it comes to clustering flows (Soriguera, 2012) and expected to apply to active travel modes. There was evidence in cycling which showed that total volumes decreased in the winter months. Therefore, the final study analyses flow which cover the entire calendar year to obtain a richer understanding of the use of these schemes.

Some limitations of the research in the second study are listed below:

- Up until the 16/11/2020, the cameras were only recording between the hours 07:00h to 19:00h, meaning the median had to be substituted for the missing hours.

- Some of the sites, not being strategic routes, have low flow volumes, particularly within the cycling dataset. Assessing the flow profiles at busier locations may give more robust results.

- As investigated, Newcastle upon Tyne has a large student population, their return following the end of lockdown could have been a major contributor to the increase in flows, more specifically at the locations closer to the city centre.

6.10 Chapter Conclusion

The research presented in this chapter further confirms that data clustering, an analysis tool not usually applied to walking and cycle flow analysis, can be used to provide a deeper understanding of the differences within daily flow profiles, such as the prevalence of commuting in the morning and evening and non-commuting related trips which tend to take place at different times of the day. Details such as this would otherwise be lost in an analysis of total daily flow counts. Furthermore, how diurnal flow profiles changed with the move from lockdown and into the post-pandemic era is important for decision-makers needing to justify investment in facilities that promote active transport. The study builds on the findings of Study 1, by analysing both cycling and pedestrian flows during and after the UK lockdown at five low traffic measure sites across Newcastle.

Whilst differences were found between sites, overall, cycling and walking has increased. Pedestrian volumes are substantially higher than the cyclists generally, but it was the latter that proportionately witnessed the greater increase in volumes, being up 40% in the post-pandemic era compared to lockdown. The results of the cluster analysis suggested that people are returning to the norms of pre-pandemic UK, with the commuter-shaped diurnal flow profiles increasing around the city post-pandemic.

However, a limitation of the study was the lack of data from before the low traffic measures were implemented, therefore a comparison is not possible. This would have enabled an understanding of how the bridges were being used by motorised traffic as well as active modes. Moreover, pre-pandemic data would have been valuable. Therefore, neither Study 1 nor 2 is able to make a comparison between the pre-pandemic and the post-pandemic diurnal flow profiles for cycling or any other mode. This requires a dataset that contains pre and post pandemic flows, paving the way for the final study which is presented in the following chapter.

Chapter 7. The New-Norm for Vehicle and Cycling Flows

7.1 Introduction

Whilst the previous two chapters provided useful insights into fundamental changes in travel behaviour as a result of the pandemic, individually they were unable to compare what was happening before the pandemic with what is happening after the pandemic. Whilst the first study had access to historic data through the TADU database, the study was carried out before the pandemic had ended and therefore only suggested the direction cycling could be heading post-pandemic. The second study used data collected at sites that were a fast-response reaction to the EATF scheme, therefore there was no opportunity to collect data beforehand, therefore, only a comparison between the pandemic and post-pandemic could be made.

This chapter presents the final of the three studies that comprise this thesis and unlike the previous two chapters, it is able to compare the pre-pandemic with the post-pandemic period. TADU was revisited and data extracted from the beginning of 2019 through to the end of 2022. This chapter also addresses the omission of vehicle traffic from the thesis. As the biggest contributor to congestion and other negative externalities of transport, it is often the most important mode to consider in many fields of transport planning. Fundamental shifts in vehicle traffic are therefore of the most interest for many transport practitioners.

Building on the new skills developed during the analysis of the second study, R is again chosen to perform the clustering with k-means being the chosen clustering method after comparing with hierarchical across three indices: Silhouette, WSS and Gap Statistic, although it was demonstrated that the difference between the two methods was minimal.

7.2 Overview of Method

7.2.1 Data selection

The initial screening of the data was carried out to identify a) sites where both motorised vehicles and cycles are recorded in parallel with each other, and b) which of these sites were likely to have been fully operational during the study period (2019-2022). Initially a total of 29 sites each counting both cycles and vehicles separately were identified across Tyne and Wear. Further screening throughout the data preparation stage found a further ten of these sites had missing data not initially identified, or with unsuitably low flows to produce representative flow profiles, leaving 19 sites for the analysis. The sites used in this study are shown in Figure 7.1, and the breakdown of total available days of data per site is shown in Table 13 below.

Table 13. Data Availability by Site

Site	2019	2020	2021	2022	Total	% Present
BEVERLEY TERRACE CULLERCOATS N OF BEVERLEY GD	285	287	301	250	1123	0.77
BRIDGE STREET, SEATON BURN	316	278	301	290	1185	0.81
BYKER BRIDGE, 20M E OF STODDART STREET	334	279	225	222	1060	0.73
EASTERN AVENUE TVTE 100M WEST OF EARLSWAY	247	204	277	219	947	0.65
FATFIELD BRIDGE (ON S.W. SIDE)	309	359	357	301	1326	0.91
GREAT NORTH RD N OF HOLLYWOOD AVE	301	287	237	254	1079	0.74
HANDY DRIVE (WESTERN RIVERSIDE ROUTE)	177	173	7	272	629	0.43
JESMOND ROAD, 100M N.E. OF AKENSIDE TERRACE	21	281	336	251	889	0.61
OLD DURHAM ROAD S OF VALLEY DRIVE	165	260	244	168	837	0.57
QUEENSWAY TVTE 80M SOUTH OF B1426 LOBLEY HILL	236	234	211	171	852	0.58
SCOTSWOOD ROAD EAST OF DUNN STREET	336	363	92	81	872	0.60
SPA WELL ROAD N.E. OF WINLATON MILL	244	289	318	271	1122	0.77
STATION ROAD, PERCY MAIN, 100M S. R/BOUT	306	299	215	205	1025	0.70
SUNDERLAND HIGHWAY, W OF A19	221	182	257	247	907	0.62
SUNDERLAND ROAD S OF MOOR LANE	287	290	306	199	1082	0.74
TANNERS BANK(FISH QUAY)	298	337	323	308	1266	0.87
TYNE BRIDGE (ON NORTH SIDE)	91	350	355	338	1134	0.78
Wearmouth Bridge	106	357	354	217	1034	0.71
WHITBURN ROAD, N OF SOUTH BENTS AVENUE	199	310	303	186	998	0.68
All Sites	4479	5419	5019	4450	19367	0.70

It can be seen that some sites in particular, namely Jesmond Road, Tyne Bridge and Wearmouth Bridge have a low count of valid days in 2019, with 21, 91 and 106, respectively. In 2021 Scotswood Road and Handy Drive feature a reduced number of counts, with 92 and 7, respectively. In 2022, Scotswood Road is also low with 81 daily flows recorded over the year. The impact of this will limit the findings at these sites in particular.

7.2.2 Data cleaning

Where days had missing hours of data, an upper limit of five blank or inappropriate zero values were identified and flagged and subsequently deleted prior to the aggregation which was found to be effective in the study by Shafique (2022). All zero counts were considered legitimate values. Linear interpolation was used on flow profiles with at least one and up to five blanks to enable them to be included for the clustering.

Linear interpolation (LI) was chosen to impute missing hourly flows over methods such as the mean or median for a given hour as LI only takes into consideration the individual flow profile. Other methods, such as substitution of the historic mean, assume flows measured in the past are representative of the missing data, considering the day of the week, seasonality trends, irrespective of whether pre- or post-pandemic. This is inappropriate in this study given the aim is to investigate the changes in diurnal profile of the traffic and cycle flows day to day due to the pandemic. LI does not consider any of these factors, at its most basic, it takes the mean value between the count for the hour before and the hour after for that given profile. Linear interpolation was carried out using the 'na.approx' function from the 'zoo' R package.

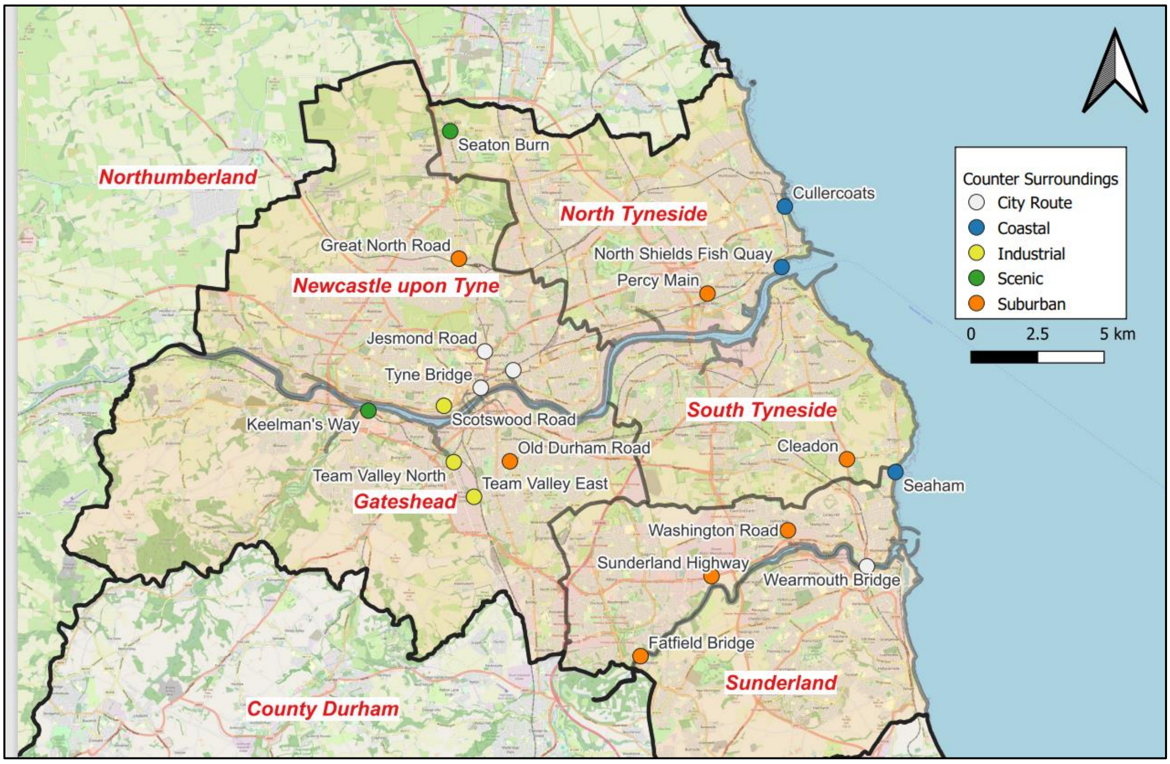

Figure 7.1. Third Study Counter Locations

7.2.3 Aggregation of Directions

The diurnal flow profiles of opposing traffic were merged. Any paired diurnal flow profiles where one direction possesses more than five blank hours or has recorded '0' across every hour of the day was removed from the dataset. The resulting dataset consists of 19,882 cycling flow profiles and 19,367 vehicle flow profiles across the 20 sites between 2019-2022.

7.2.4 Normalisation

Informed by the methodological review chapter, the diurnal flow profiles were normalised, according to the relationship between the recorded hourly flow and the mean average for that specific day and site.

7.2.5 Selection of clustering method

Hierarchical and k-means were identified in the methodological review section as the most common methods to cluster diurnal flow profiles. The dataset for Study 3, covering four, full years of diurnal flow profiles, required significantly more computational power than Studies 1 and 2. As a result, the industry-standard computer used for this research was unable to perform hierarchical cluster analysis on the high-dimensional dataset, so alternatives were explored. As explained in Section 3.6.3, k-means has been found to require less computational effort in order to be performed (Sharma et al., 2012; Ghosh & Dubey, 2013; Karthikeyan et al., 2020; Gupta et al., 2021), therefore this methodology was tested on the dataset, and was successful.

After separating the flows based on the mode, all sites and days across the four-year study period were clustered together, maintaining the novel aspect to the study as previous research generally pre-classifies the data according to site or day of the week and do not cover such a long time period, particularly one that covers something as significant as the pandemic.

Once the diurnal flow profiles were assigned to clusters, much like the previous two chapters, the characteristics of the clusters were compared considering the day of the week they fell on across the study years. The emerging patterns were scrutinised in the context of the post-pandemic period and the outcomes discussed in the context of policy as well as comparison with other studies into post-pandemic travel patterns. In the sections that follow, the results of the vehicle and cycle are presented and discussed together.

7.3 Results

7.3.1 Change in Pre- and Post-Pandemic Volumes

Firstly, the average monthly flows between 2019 and 2022 are plotted in Figure 7.2. The monthly flows are normalised across the four years to enable a comparison between vehicles and cycling flows.

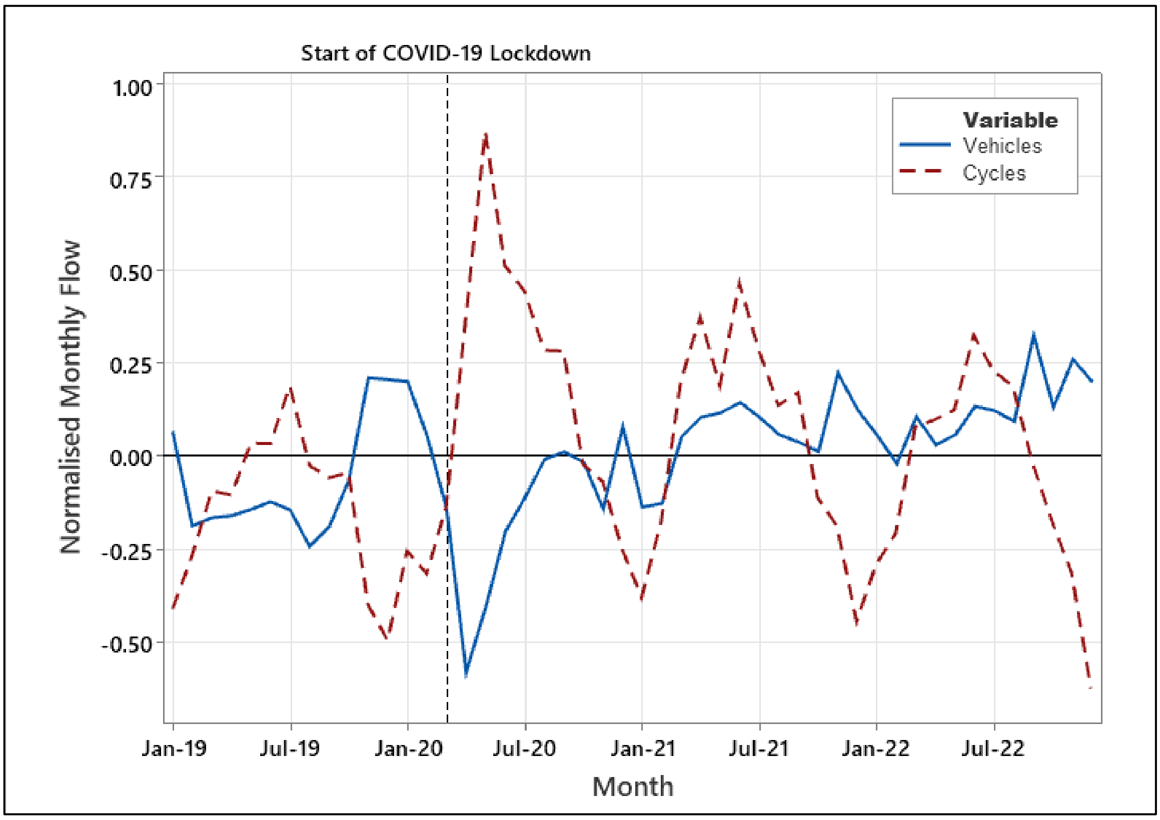

Figure 7.2. Effect of COVID-19 on Flow Volume across Case Study

It can be seen in Figure 7.2 that the introduction of COVID-19 lockdown restrictions in March 2020 has the opposite effect on cycles and vehicles. Whilst motorised vehicles saw a decrease, cycles saw a spike in usage. Similar to Study 2, cycling flows show the most seasonality whether pre, during or post pandemic. 2020 sees the highest summertime peak, with a drop in 2021 and a further drop in 2022, however these remain higher than the summer 2019 peak. This is comparable to the annual trends seen in Figure 2.2 of the literature review chapter. The results are presented in Table 14.

Table 14. Results comparing 2019 and 2022 Average Flow Volume

Mode	2019 Mean	2022 Mean	Change in Mean	St Dev	SE Mean	95 % CI
Vehicles	17,592	17,581	-11	4211	966	-2,040, 2,018
Cycles	176.4	206.8	30.4	72.4	16.1	-3.3, 64.1

Based on the average change in daily volume of just -0.06%, it is concluded that motorised vehicle flows have returned to pre-pandemic levels. On the other hand, cycling flows remain 17% higher on average in the post-pandemic. Cluster analysis of the diurnal flow profiles will provide additional insight as to whether the return of traffic has occurred evenly across each hour of the day and day of the week.

To determine whether there is variation within the sites, Figure 7.4 plots the 2022 average daily cycle volumes at each site against 2019. The same comparison is made for vehicles in Figure 7.5.

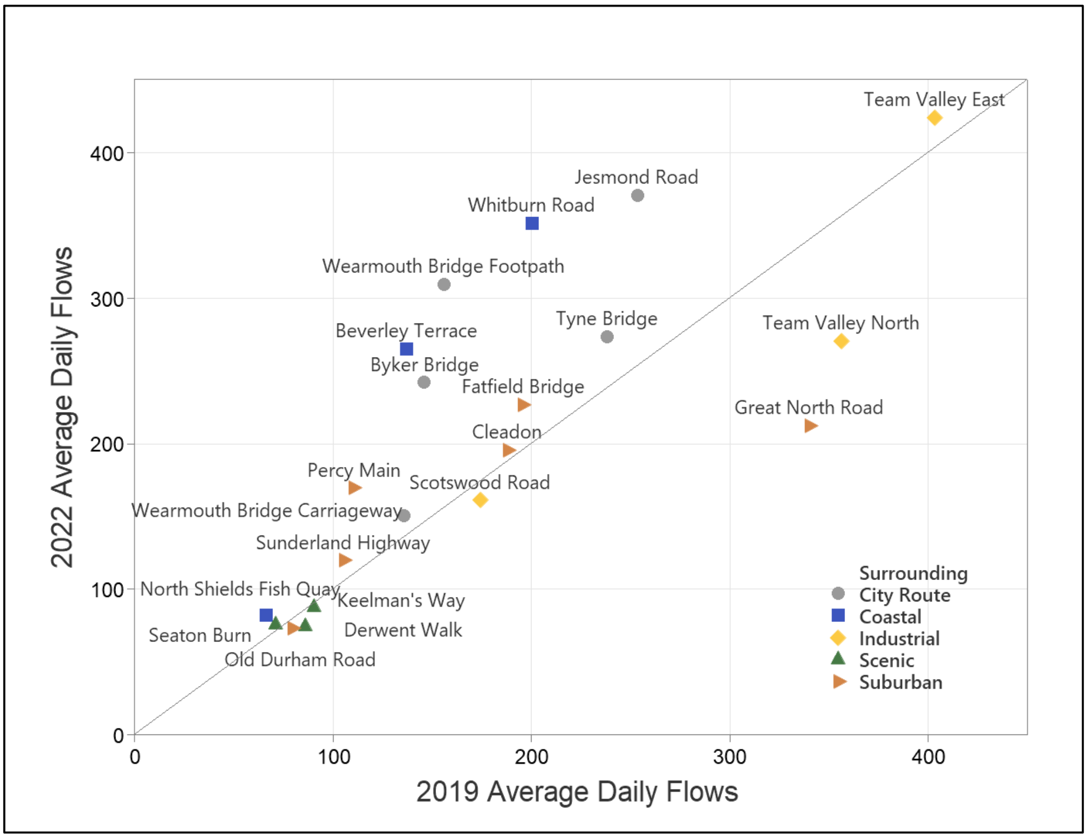

Figure 7.3. Pre and Post Pandemic Change in Cycle Volumes

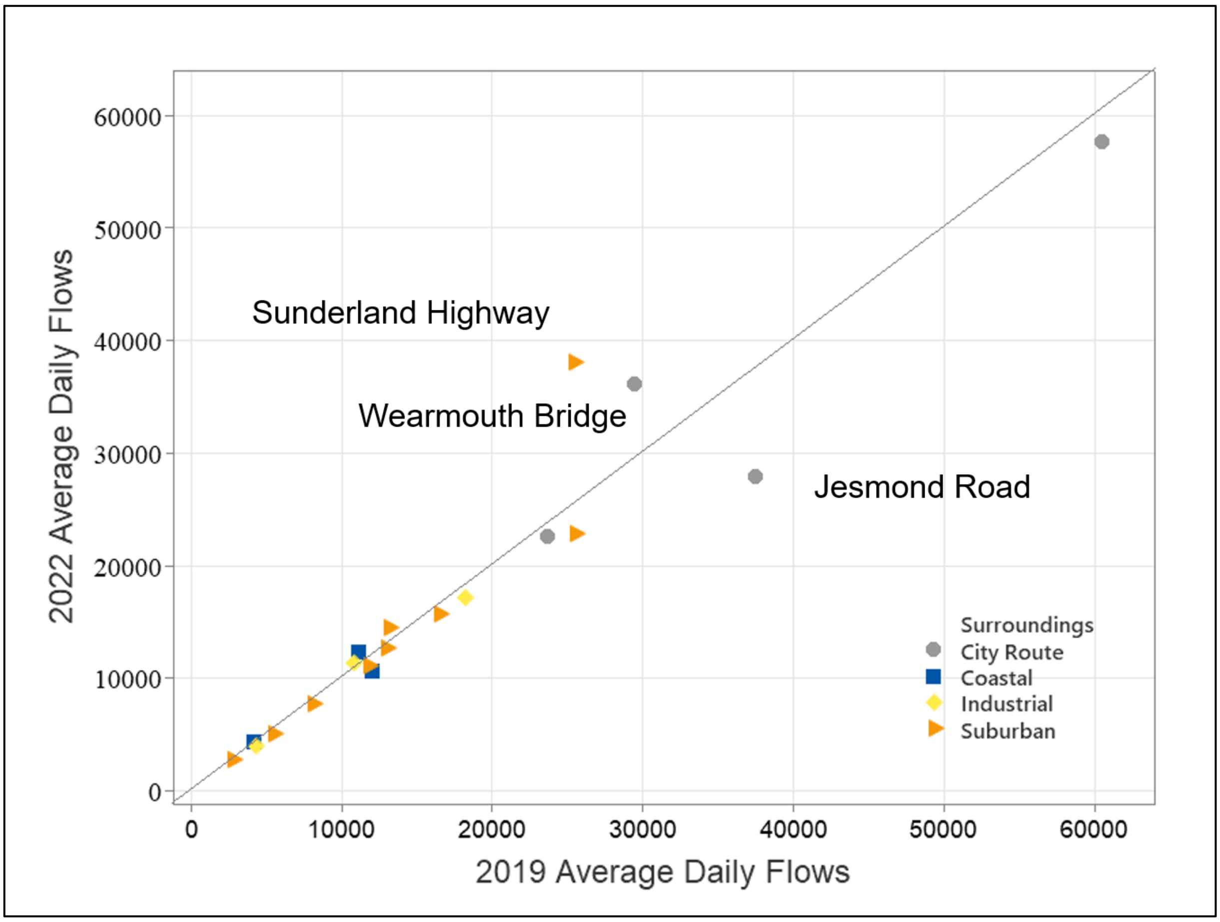

Figure 7.4. Pre and Post Pandemic Change in Vehicle Volumes

Figure 7.4 shows that across the vehicle dataset, 2022 flow volumes are very similar to the pre-pandemic levels of 2019, with most sites sitting close to the Y=X line. Further examination of Table 13 finds that Jesmond Road, a city centre site that experiences the largest decrease in the post-pandemic data, only has 21 days of valid data from 2019, which could make the results unreliable. With regards to the cycling flows in Figure 7.3, the differences pre- and post-pandemic flow volumes show greater variation than the vehicles, with increases at 14 of the 20 sites studied with decreases ranging from across 6 sites. These results demonstrate the importance of extending the study period to the end of 2022 for a true insight into the post-pandemic when compared with some of the findings in Study 1 (end of August 2020). To recap, one of the key findings was that during and immediately after the pandemic, the city centre locations saw a large decrease in total cycle volume when compared to the pre-pandemic flows. However, Study 3 shows that after two years, these flows have not only recovered, but they have increased on 2019 volumes at these sites, with Jesmond Road, Wearmouth Bridge, Byker Bridge and Tyne Bridge all showing overall increases in cycling. The popularity of cycling remains on the coast, with the two sites located directly on the seafront, Beverley Terrace and Whitburn Road, showing considerable increases. The next step was to investigate changes in the diurnal profiles for each mode.

7.3.2 Determining the number of Clusters

As with the previous two chapters, determining the number of clusters is guided by indices but ultimately is a subjective process. Using R, the, Silhouette plot, WSS and Gap statistic were plotted for vehicles and cycling across a range of cluster solutions and presented in Figures 7.6 and 7.7, respectively.

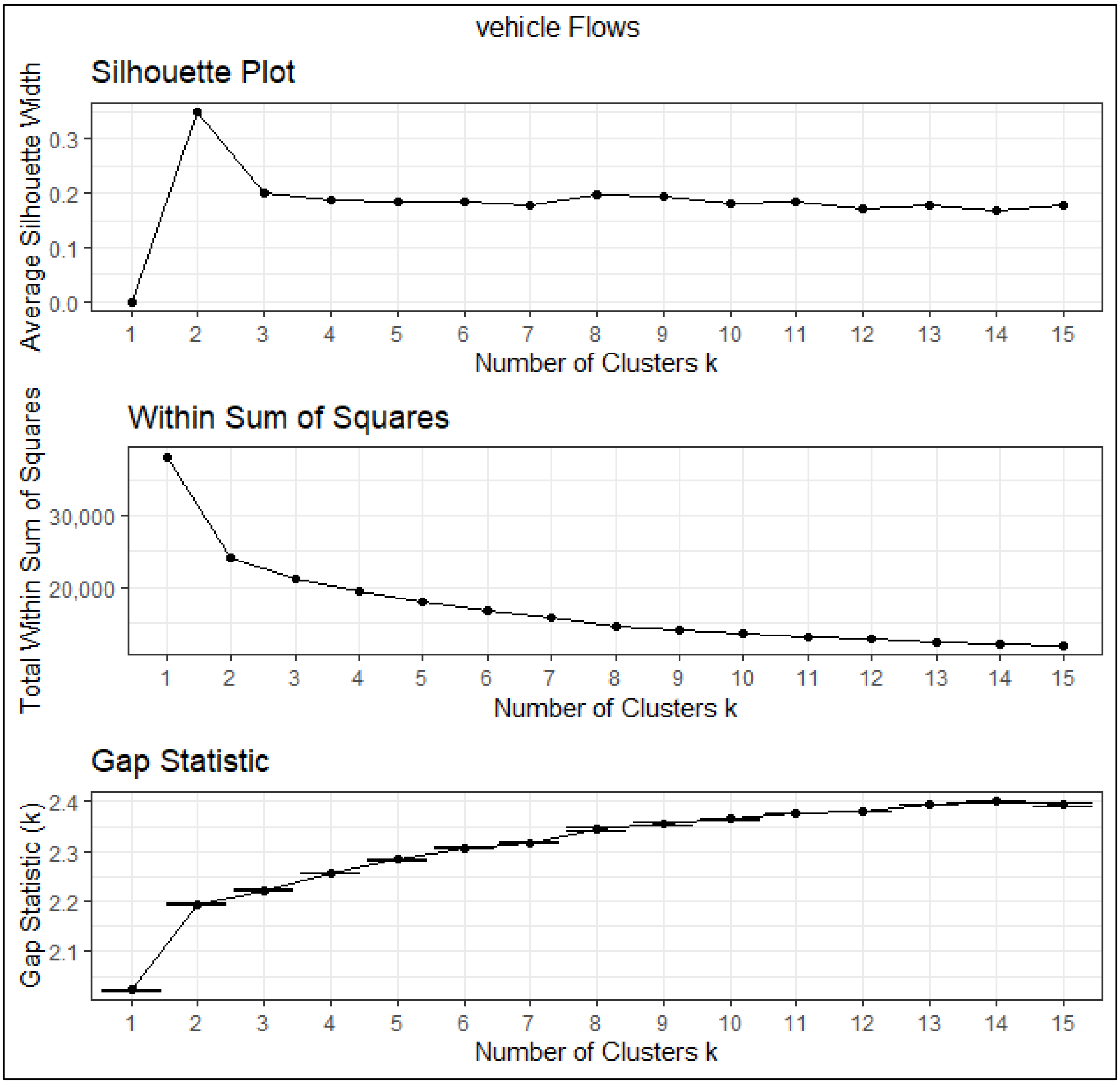

Figure 7.5. Defining N of clusters with indices (vehicles)

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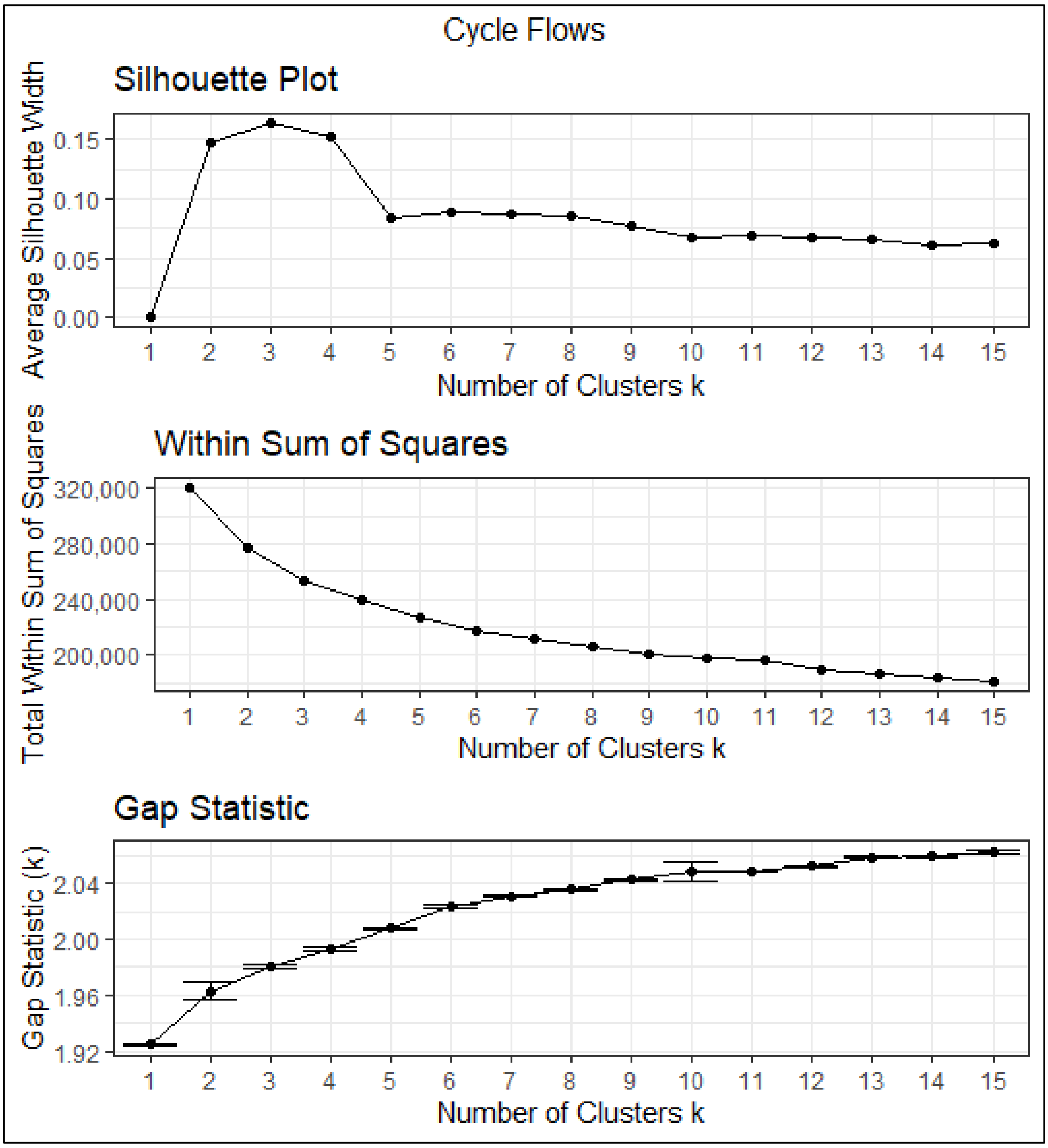

Figure 7.6. Determining N of Clusters (cycles)

Figures 7.5 and 7.6 suggest that statistically, the optimal number of clusters is very low. For vehicles, Figure 7.6 would suggest a two-cluster solution appears to be optimal, with the peak of the Silhouette plot and the elbows of the WSS and Gap plots falling at this point. The previous literature covered in Chapter 3 and findings within the two chapters that preceded this chapter inform that there is little insight that can be produced from a two-cluster solution of diurnal flow profiles. The results of the cycling clustering test results presented in Figure 7.6 are more ambiguous, with two, three or four cluster solutions appearing the strongest statistically with average silhouettes of approximately 0.15 and no obvious elbows across the WSS and Gap Statistic plots.

Without a conclusive answer arising from the indices that would also provide meaningful discussion, it was decided to cluster the data in turn from four upwards and take high-level observations of the results before deciding on the preferred number to use. For the cycling diurnal profiles, eight clusters were found to be a good compromise that allowed enough clusters provide meaningful discussion. The larger number of clusters than the previous chapters was in part due to two small, niche clusters forming. Using this methodology for the vehicle flow clustering, coincidently an eight-cluster solution was also found to be the optimal solution.

7.3.3 Vehicle Pre- and Post-Pandemic Diurnal Flow Profiles

The diurnal flow profiles at each site for each day over the study period of 2019-2022 were clustered into eight groups using *k*-means. Firstly, the silhouette index is plotted, each colour representing a cluster (Figure 7.7). This shows well each diurnal flow lies within their assigned cluster. The average silhouette value for the vehicle diurnal flow clustering is 0.19. The bigger the area above silhouette index value of 0.0 the higher the similarity within and difference between clusters

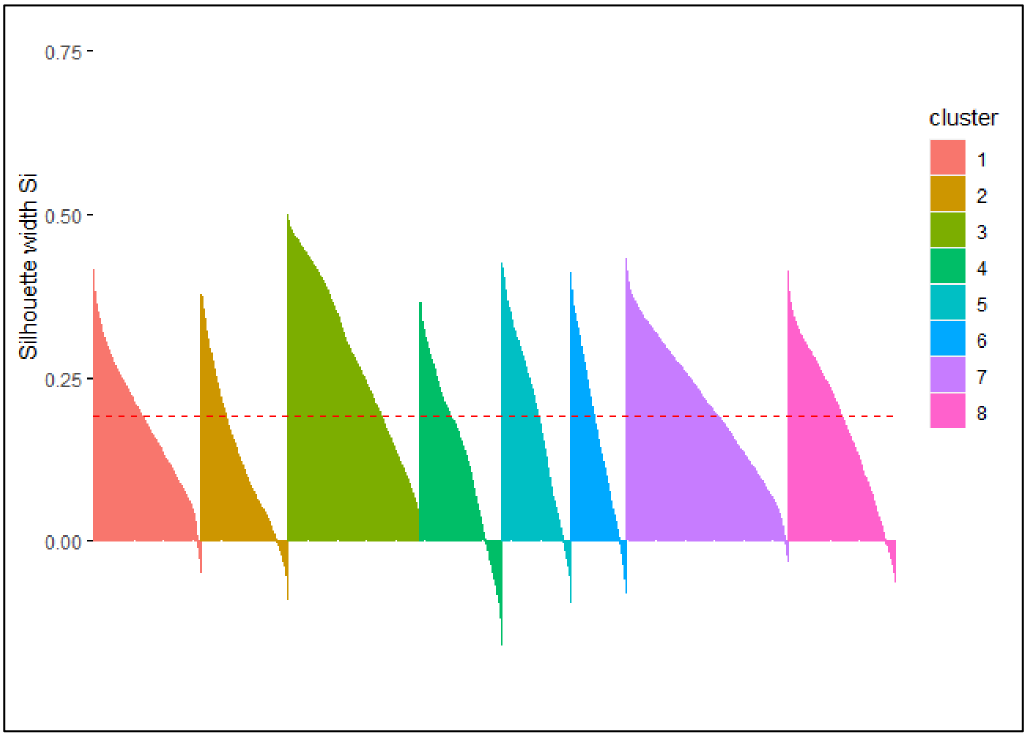

Figure 7.7. Vehicle Silhouette Profile

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Figure 7.8 presents both the mean average diurnal flow profile and a ribbon representing two standard deviations from the mean to illustrate the representativeness of each average flow profile to the overall cluster, colour-coded in sync with the Silhouette plots in Figure 7.7. Table 15 compares the pre (2019) and post (2022) pandemic years, which is the primary focus of this chapter.

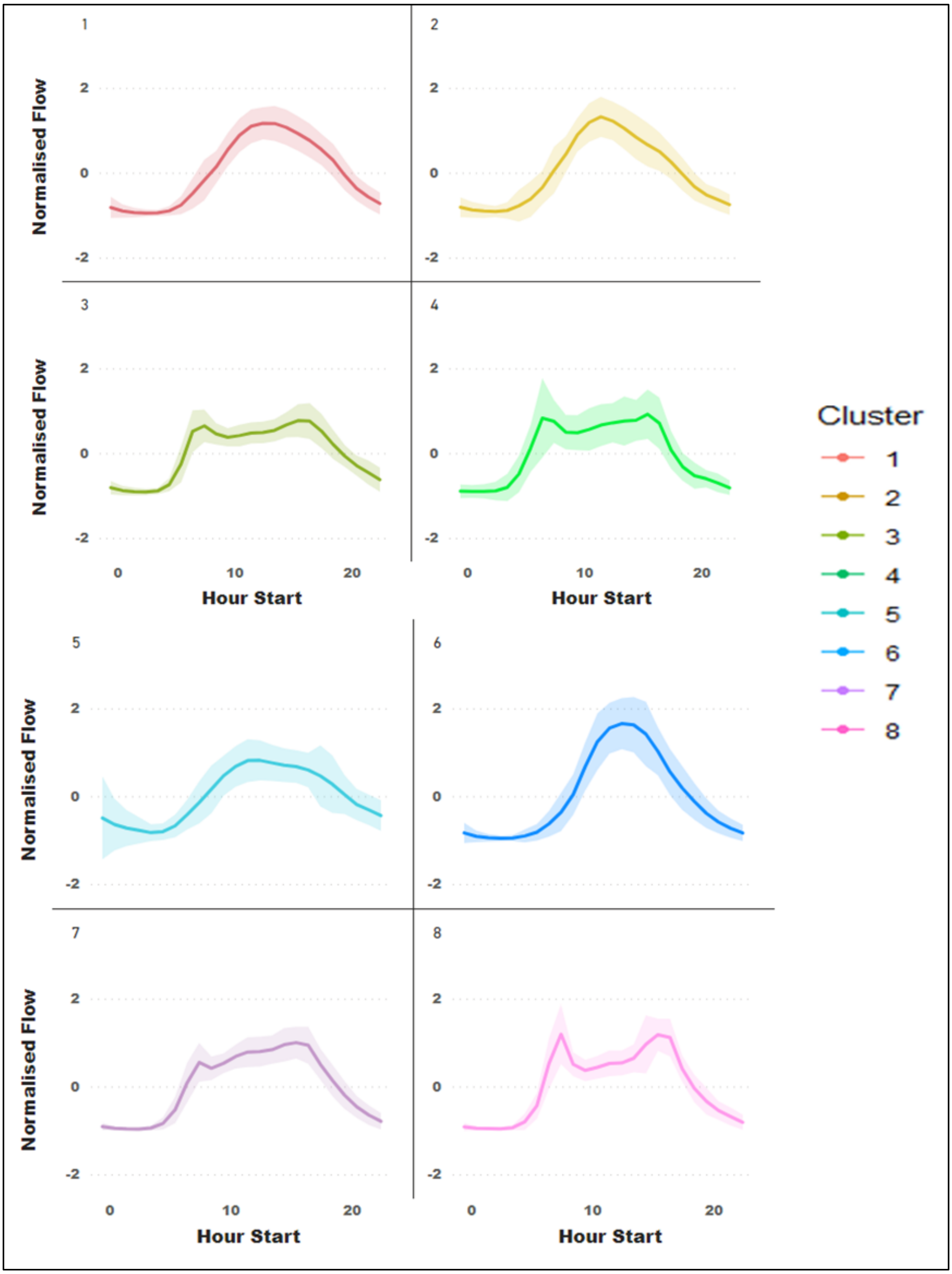

Figure 7.8 Vehicle Cluster Profiles to 2 Standard Deviations

Table 15. Overview of Vehicle Clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8
Shape	Early PM Flat Peak	Mid-Day Peak	AM and PM Peak with Gradual drop-off	AM and PM Peak with steeper drop-off	Mid-Day Flat Peak	Early PM Sharp Peak	PM Peak	AM and PM Sharp Peaks
Peak Hours	12:00-16:00	11:00-14:00	08-09 & 16-18	07-08 & 16-17	12:00-14:00	12:00-16:00	16:00-17:00	08-09 & 16-18
W.S.S.	1,677	1,823	1,597	2,300	2,174	1,460	1,956	1,638
Sil. Width	0.178	0.179	0.280	0.132	0.187	0.160	0.209	0.179
Yearly Totals								
2019	440	532	792	387	402	208	866	852
2020	894	524	746	634	323	481	1,228	589
2021	750	533	787	613	354	401	1,000	581
2022	516	498	881	341	585	245	823	561
Total	*2,600*	*2,087*	*3,206*	*1,975*	*1,664*	*1,335*	*3,917*	*2,583*
2022 Totals (% change from 2019)								
Monday	48 (23%)	28 (-22%)	137 (10%)	61 (9%)	33 (175%)	25 (178%)	156 (-1%)	122 (-36%)
Tuesday	34 (62%)	23 (-23%)	185 (21%)	64 (-6%)	26 (189%)	5 (0%)	161 (5%)	128 (-38%)
Wednesday	41 (78%)	17 (-32%)	193 (24%)	65 (-12%)	26 (420%)	2 (-33%)	166 (-2%)	126 (-33%)
Thursday	39 (8%)	27 (80%)	197 (13%)	65 (-10%)	40 (1233%)	5 (67%)	149 (-10%)	119 (-31%)
Friday	57 (46%)	22 (29%)	169 (-8%)	74 (-20%)	60 (567%)	7 (250%)	190 (-12%)	66 (-30%)
Saturday	152 (12%)	239 (-1%)	0 (-100%)	11 (-50%)	223 (6%)	22 (-12%)	1 (-67%)	0 (0%)
Sunday	145 (-1%)	142 (-15%)	0 (0%)	1 (-67%)	177 (16%)	179 (11%)	0 (0%)	0 (0%)

Table 15 shows there are no overly niche clusters in the vehicle data, which can be prone to developing using k-means when compared to Ward's hierarchical approach. Cluster 6 (C6) possesses the lowest membership with 1,664 flow profiles and is heavily associated with one particular day (Sunday) as well as during midweek in the pandemic years. Conversely, the largest Cluster, 7, is associated with more days (Monday to Friday) and is characterised by a PM peak higher than its AM and with trips steadily occurring in between. This profile increased in prevalence during the lockdown years and returned to similar pre-pandemic levels in 2022.

Cluster 1 is the third most common profile, with a four-hour flat peak across mid-day seeing increased numbers during the pandemic and although its frequency decreased in 2022, it still remained 17% higher than pre-pandemic levels. Whilst it remains more common on weekend days, there is less difference between those and weekdays in the post-pandemic, with 58% increases in occurrences on Wednesday and 65% increase on Thursday.

Clusters 3 (C3) and 4 (C4) both with AM and PM peaks make an interesting comparison as they both feature AM and PM peaks and are associated with weekdays, but with subtle differences. Firstly, C3's peaks are not as sharp as C4's. Both their AM peaks cover the hours 07:00-09:00, however the absolute AM peaks are 08:00-09:00 and 07:00-08:00, respectively. C3 possesses a flatter PM peak between 16:00-18:00 compared to Cluster 4's 16:00-17:00. When comparing the pre-pandemic values with the post-pandemic it is apparent that C3 has increased in prevalence by 11% whereas C4 has decreased by 12%, suggesting a trend towards later morning peaks, and longer, later evening peaks with both contributing less to the overall daily flow than pre-pandemic.

Cluster 8 (C8) exclusively falls on the working week and with the sharpest AM and PM peaks could be labelled as the most traditional working day, with a 9-5 commuter shape. As would be expected during the pandemic era these peaks reduce, however whilst they have since increased in 2021 and 2022, they have not bounced back to pre-pandemic levels. They remain less prevalent on Fridays, just as they were in pre-pandemic era. A comparison of C8 prevalence with C7 across the study period is shown in Figure 7.9.

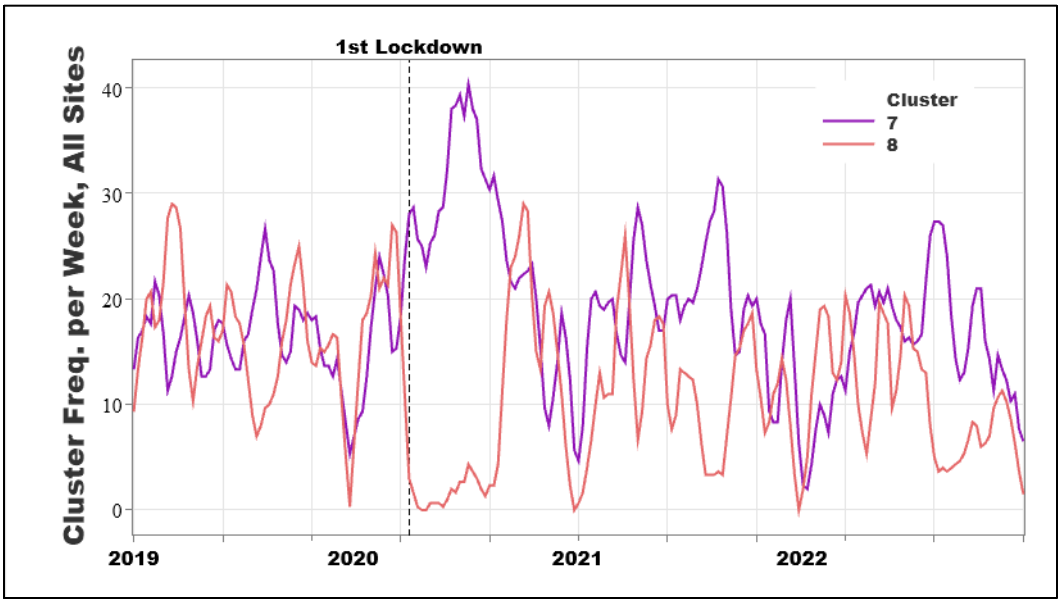

Figure 7.9. Vehicle C7 and C8 Prevalence, 2019-2022

Clusters 2 (C2) and 5 (C5) are both associated with the weekend, although C5 becomes substantially more prevalent on weekdays in the post-pandemic era when compared with C2. It possesses a flatter peak and a more even distribution of flows across the day than C2, which has a sharper peak that forms earlier in the day.

Examination of the clustering results suggests that the fall in C8 and rise of C7 during the lockdown of 2020 (shown in the line graph in Figure 7.9), are related. flows that were C7 on a given day and site during lockdown were C8 the previous year.

Overall, it can be seen that differences between weekdays and weekends are less distinguishable in terms of shape of the diurnal profile in the post-pandemic era for vehicle traffic. In addition, the traditional morning and evening commute flows are not just occurring on fewer days but typically they are not as pronounced post compared to pre pandemic. Also, peaks are contributing less to the total daily volumes which are more spread over a wider time period.

7.3.4 Cycle Pre- and Post-Pandemic Diurnal Flow Profiles

Cycling flows are presented in this section, starting with the Silhouette profile (Figure 7.10) and the average cluster profiles (Figure 7.11).

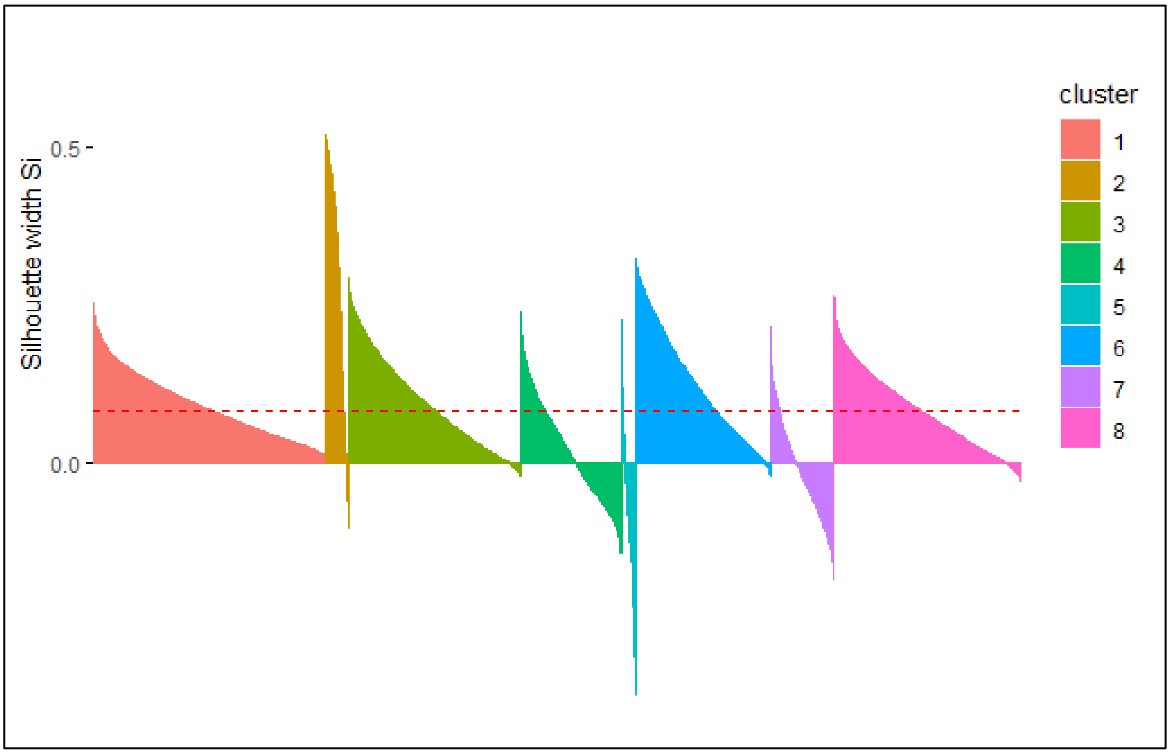

Figure 7.10. Silhouette plots cycling

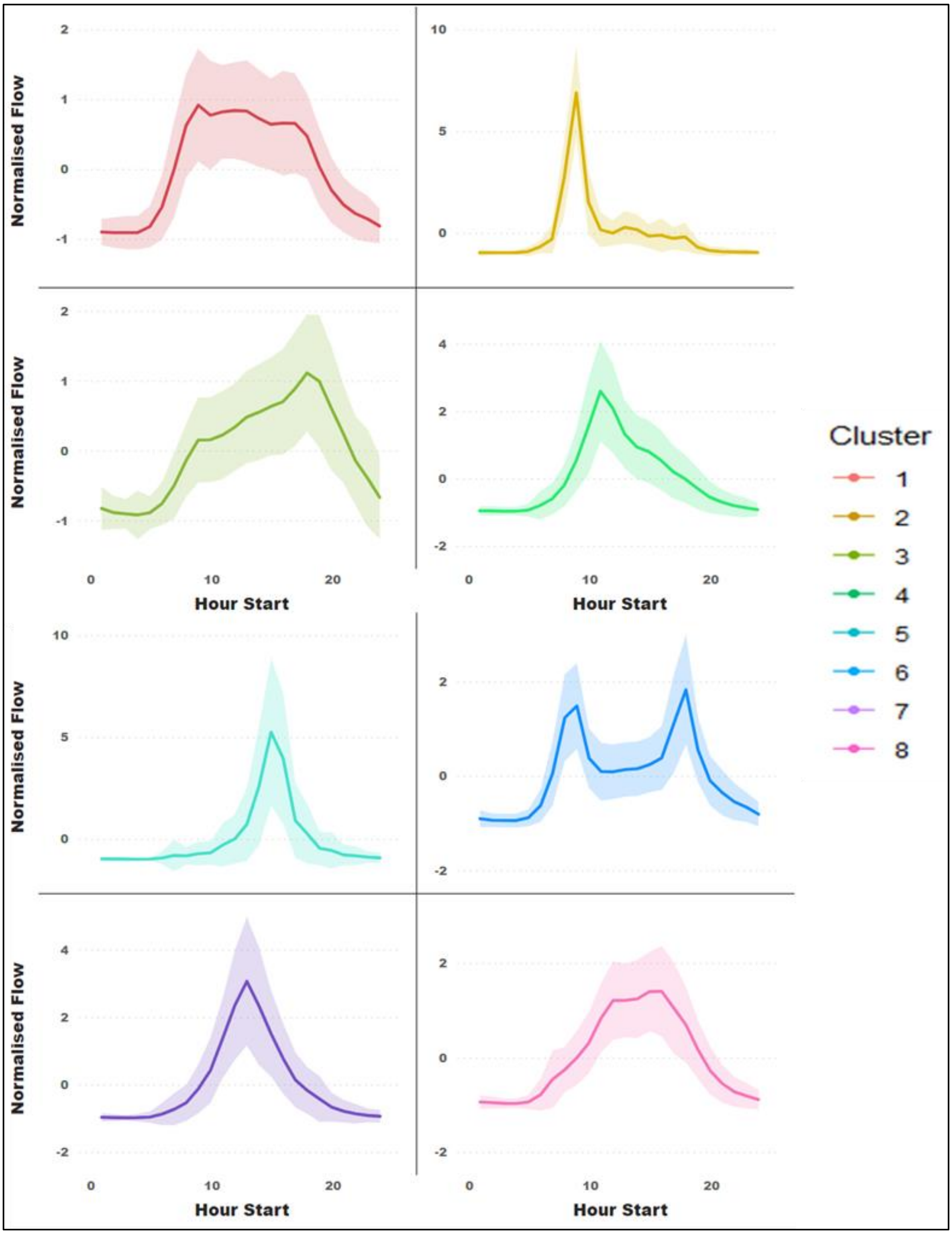

Figure 7.11. Av. Cycle Cluster Profiles to one Standard Deviations

Unlike the vehicles, it was decided to also present the average diurnal flow profiles to one standard deviations. The silhouette diagram already demonstrates that there is more variation within the cycling flows and plotting the standard deviations confirms this, with the ribbons representing two standard deviations a lot wider, shown in Appendix B.3.

Table 16. Overview of Cycle Clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8
Shape	Flat	AM Very Sharp Peak	Rises Steadily All Day	Mid-AM Peak	Mid-PM Very Sharp Peak	AM & PM Peak	Mid-Day Peak	PM Plateau
Peak Hours	12:00-16:00	08:00-09:00	17:00-18:00	10:00-11:00	14:00-15:00	08-09, 17-18	12:00-13:00	11:00-16:00
W.S.S.	37,749	7,715	34,276	28,688	15,008	25,100	24,240	-0.014
Sil. Width	0.092	0.299	0.095	0.019	-0.071	0.123	-0.014	0.083
Yearly Totals								
2019	1,031	182	766	499	55	1,116	329	697
2020	1,339	65	1,059	602	97	647	404	1,508
2021	1,354	94	1,082	565	99	548	382	1,083
2022	1,256	142	796	477	70	573	263	702
Total	*4,980*	*483*	*3,703*	*2,143*	*321*	*2,884*	*1,378*	*3,990*
2022 Totals (%change from 2019)								
Monday	180 (21%)	22 (-29%)	122 (44%)	49 (26%)	7 (40%)	107 (-52%)	21 (-30%)	86 (-12%)
Tuesday	218 (31%)	29 (-22%)	103 (-8%)	20 (-38%)	14 (367%)	137 (-42%)	12 (-54%)	68 (-1%)
Wednesday	202 (58%)	32 (-9%)	118 (-2%)	36 (29%)	9 (0%)	139 (-47%)	13 (-41%)	64 (2%)
Thursday	223 (65%)	27 (-31%)	90 (-16%)	43 (2%)	9 (29%)	119 (-48%)	18 (-14%)	88 (4%)
Friday	231 (13%)	27 (-25%)	98 (11%)	53 (29%)	16 (45%)	56 (-64%)	28 (8%)	112 (10%)
Saturday	125 (-28%)	4 (100%)	128 (7%)	118 (-13%)	9 (13%)	11 (83%)	76 (-15%)	150 (8%)
Sunday	77 (1%)	1 (-50%)	137 (2%)	158 (-13%)	6 (-50%)	4 (33%)	95 (-17%)	134 (-5%)

Similar to the overall flow volumes, there is more variation in the diurnal profiles across the cycling compared to the vehicles data. Clusters 2 (C2) and 5 (C5) have peaks much greater than the other clusters, far greater than differences within the vehicle flows. These are infrequent with 483 and 321 diurnal flow profiles in each, respectively. C2 is associated with an extremely sharp morning peak between 08:00h and 09:00h on working days at one site in particular adjacent to a large light industrial business park. C5 is identifiable by its slightly less extreme early afternoon peak and is spread across a range of sites.

Cluster 1 (C1) has a flat shape across the day and is the most common diurnal profile in cycling for every year apart from the pre-pandemic year, appearing on 4,980 occasions in total. This shape increased in prevalence over the lockdown, reducing slightly in the post-pandemic period but still 22% higher than in 2019. There has been a shift in how these flows are distributed across the week, with the increases of this flat diurnal flow profile occurring on weekdays. Sunday remained similar but Saturday saw 28% fewer of C1.

Whilst C1 was the most common in 2020, 2021 and 2022, the AM and PM peaked profile of Cluster 6 (C6) was most prevalent in the pre-pandemic period. Similar to the traditional commute shape of C8 in the vehicle dataset, the cycling AM & PM peak profile reduces during the pandemic era and does not return to pre-pandemic levels afterwards. Monday (-52%) and Friday (-64%) have seen greater reductions than other weekdays. Appendix B compares their change in prevalence during the study period.

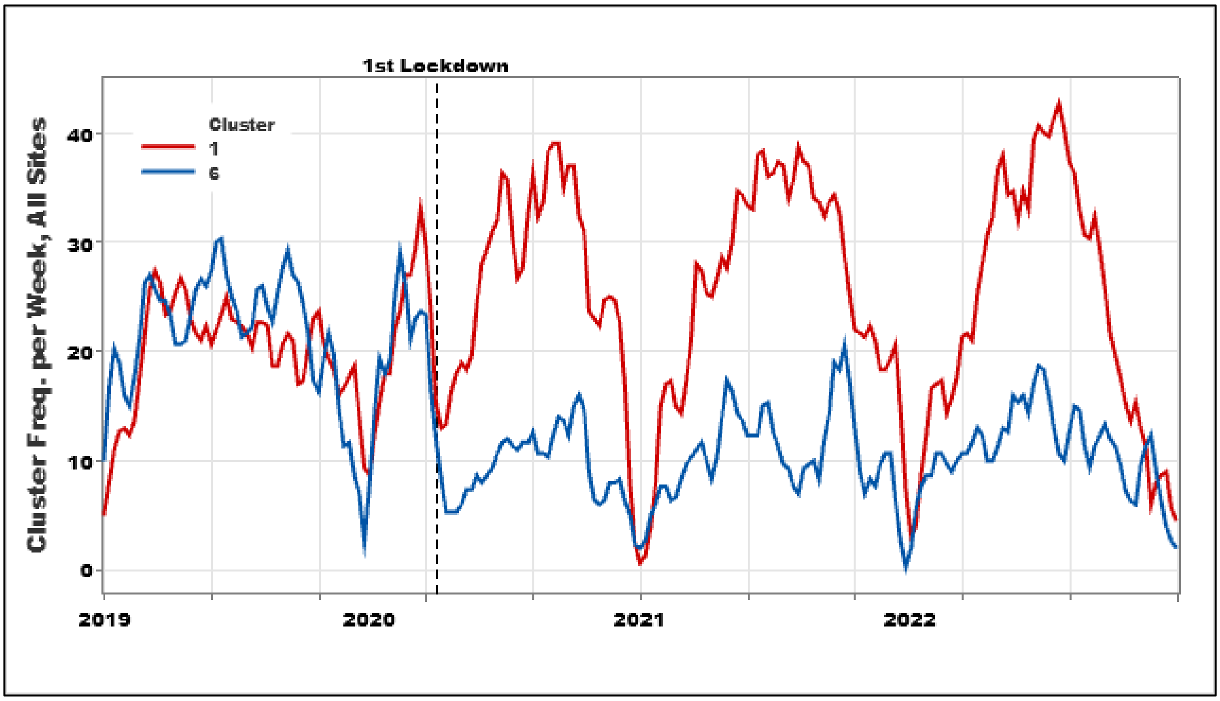

Figure 7.12. Cycle C1 and C6 Prevalence, 2019-2022

Cluster 8 (C8) is the second largest group. The shape of the profile can be described as an ‘afternoon plateau’, with flows rising until 11:00h and remaining steady until 16:00h before declining. C8 is more common over the weekend, followed by Monday and Friday, in comparison to the other weekdays. C8 increases during the pandemic but returns to pre-pandemic prevalence in the post-pandemic. Similarly, Cluster 3 (C3) has a profile that gradually rises over the day, peaking at 17:00h-18:00h and occurs across the week. Similar to C8, after a slight increase during the pandemic, C3 returns to pre-pandemic levels in the post-pandemic.

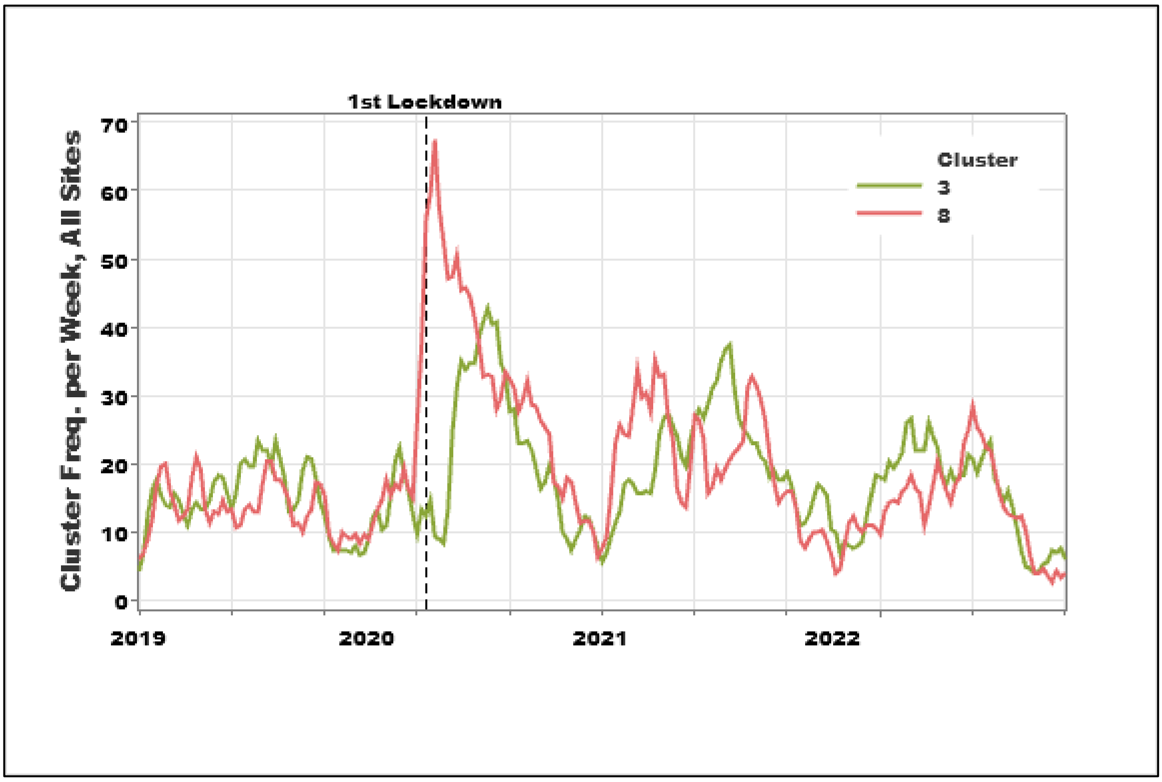

Figure 7.13, Cycle C3 and C8 Prevalence, 2019-2022

Clusters 4 (C4) and 7 (C7) both have peaks in the middle of the day, are more associated with weekend flows and their prevalence has decreased slightly in the post-pandemic era when compared to pre-pandemic levels.

In summary, for cycle flow clusters, the most significant decrease in diurnal profile is of the traditional AM & PM peak shape of C6, which became less frequent during lockdown and has not returned. This is particularly noticeable on Fridays. Whilst the flatter profile of C1, with levels spread across the day, has increased in frequency during the weekdays post-pandemic, C4 and C7 with the sharper mid-day peaks have returned to pre-pandemic volumes. This suggests that on more days in the post-pandemic era there could be a bigger range of journey types being made, not just commutes and not just outings during the middle of the day but a mix of everything.

7.4 Discussion

In this section the results are considered across both modes focussing on a comparison of the year 2019 with year 2022 reflecting on previous research in this area.

7.4.1 Suitability of Methodology

As found by Weijermars & van Berkum (2005) without pre-classification by day of week, the variation within clusters was found to be quite large, particularly in the cycling flows. This is to be expected with clustering 20 sites together over such a long time period and no pre-classification by the day of the week. Additionally, the counters themselves are sited at a range of locations from recreational trails to on-road often used by commuters into the city. The advantage of not pre-classifying, however, is that all days are clustered together, allowing any similarities or differences to cluster freely regardless of the day of week or whether it occurred pre, during or post-pandemic. This is what has allowed the discovery of fundamental understandings from this study.

The large difference in the average daily flows across the locations within both the vehicle and cycling data as shown in Figures 7.3 and 7.4 illustrates the need to normalise the hourly flows for the diurnal flow profiles when studying more than one site. Without doing so, the volumes would have been the dominant factor in determining dissimilarity through larger Euclidean distances between points.

The k-means method of clustering appropriately identified and separated the niche Clusters 2 and 5 in the cycling dataset where Ward's method of hierarchical clustering, as used in Weijermars & van Berkum (2005), may have converged with other clusters to ensure more equal-sized clusters, a characteristic of that particular clustering method.

7.4.2 Outcomes

Considering vehicle flows, the results suggest that mean total daily volumes of traffic in 2022 are back to pre-pandemic levels, with a difference across the 19 sites of just -0.06%.

In the post-pandemic, there is less distinguishing of the days of the week by their typical flow profiles. Mondays and Fridays have become less similar to other weekdays, resembling a half-way between the working week and the weekend. Similar to the findings in Germany (Ecke et al., 2022), there is less dominance of the AM and PM commuter flow profiles in the post-pandemic, and the days that do possess ‘commuter shapes’ have been clustered into a group with less pronounced peaks than previous, similar to the findings in Hong Kong (Loo & Huang, 2022). Interestingly, a noticeable shift in the time of day the peaks were occurring being slightly later both in the morning and evening and spread over a longer period in the evening peak, possibly a sign of more flexible working post-pandemic.

Tyne and Wear experienced the boom in cycling during the pandemic consistent with other areas across the UK and beyond. Whilst levels dropped afterwards volumes post-pandemic remains on average 17% higher compared with the pre-pandemic. Similar to the vehicle flows, the morning and evening peak flows witnessed a reduction in prevalence in the post-pandemic era, with flatter profiles becoming more common resembling a greater mix of trip purposes and more flexible working practices. This was most noticeable on Fridays.

These findings demonstrate that a behaviour change towards cycling has occurred paving the way for policies to prioritise active travel modes which in turn will most benefit net zero ambitions. For example, this extra capacity emerging during the peaks should be used to give priority to cycling with the reallocation of road space to cycling. This can be achieved by reducing cycle times in urban areas or giving green duration to cycle stages in traffic signal-controlled areas. Also, ideally simultaneously, by creating segregated infrastructure (cycle lanes or separate cycle paths) and Low Traffic Neighbourhoods, encouraging more cycling. Without timely action, this additional capacity could be filled with induced travel demand, as the economy recovers post-COVID, population increases with associated demand for housing, jobs along with consequential need to travel.

7.4.3 Limitations and Further Study

Whilst aggregating flows to hourly counts revealed patterns across the day over a wide number of sites, a shorter duration of aggregation would reveal finer details at specific times during the day. For example, an investigation of whether the bifurcation of the morning peak observed in post-pandemic Californian cities (Gao & Levinson,

2022) had occurred in Tyne and Wear was not possible. TADU does have records of vehicle and cycles flows aggregated at 15-minute intervals therefore, this would be worth exploring in a future study, however, the number of locations would be fewer. The results from clustering the diurnal flow profiles can be explored in depth beyond the scope of this chapter – for example, how spatial elements of the counters influence the associated diurnal flow profiles. This paves the way for further studies. Worthy of note is that because there were more valid diurnal flow profiles in years 2020 and 2021 means the pandemic era is more represented than the pre-pandemic (2019) and post-pandemic (2022) for both cycles and vehicles. However, the impact of this on the findings for this particular study is limited given the focus is on the comparison of cycle and vehicle diurnal flows between 2019 and 2022.

7.5 Conclusion

The study has shown that in the post-pandemic cycling has increased in terms of volume as well as the times in the day people are choosing to travel, addressing, to some extent, those political barriers to investment in cycle infrastructure in England. Whilst total daily vehicle traffic has returned to pre-pandemic volumes, this analysis suggests that there could be more capacity on the roads during the traditional pre-pandemic AM and PM peaks because the time people are travelling has spread-out over the course of the day and week. However, evidence suggests that like vehicle flows, cycling flows are returning to pre-pandemic baseline, albeit at a slower pace. If no action is taken, induced travel demand may gradually be eroded and the window of opportunity for change to capitalise on spare capacity will be missed.

Chapter 8. Final Discussion, Recommendations and Conclusion

8.1 Introduction

COVID-19 and the associated lockdowns across the globe brought about many challenges, but also some opportunities, to the transport sector. Lockdowns drastically reduced the demand to travel, resulting in a substantial fall in motorised traffic, something that is imperative in order to achieve net zero. On the other hand, sustainable modes walking and cycling increased resulting in cities across the world providing new infrastructure to accommodate them.

As society enters the post-pandemic, some of the practices adopted during the lockdowns, such as increased WFH and online shopping, have remained, which affects not just the volume of trips made across the transport network but their spread across the day and week, potentially creating a 'new-norm'. Therefore, Chapter 1 of this thesis set out the reasoning for the following research questions addressed in this thesis:

1. What impact did the COVID-19 pandemic and resultant lockdown have on cycling volumes and diurnal flow profiles? (Study 1, Chapter 5);
2. Did cycling and walking flows change in the post-pandemic period in locations where active travel infrastructure interventions occurred during the pandemic? (Study 2, Chapter 6);
3. What are the longer-term impacts of the COVID-19 pandemic on cycling volumes and diurnal flow profiles, and to what extent can the post-pandemic period be called a 'new-normal'? (Study 3, Chapter 7);
4. How have the change in vehicle flow volumes and diurnal flow profiles differed to those of cycling between the pre-pandemic and post-pandemic era? (Study 3, Chapter 7).

The aims and objectives to address the research questions were then developed for the research. The set of research tasks to meet the aim and objectives of the research were developed and included a literature review (Chapter 2), a review of analytical methods (Chapter 3) and the development of a methodological approach capable of capturing the patterns in diurnal flow profiles (Chapter 4). The next task was to investigate the effect the pandemic had on the diurnal flows of vehicles and active travel during the lockdowns and its lasting effect in the post-pandemic period, the results of which are covered in Chapters 5-7, before summarising and discussing the findings in a wider context in Chapter 8.

Whilst each of the research questions have been discussed in their respective chapters, they will be brought together and summarised in the main findings within Section 8.2. Next, the limitations of the research will be discussed in Section 8.3, followed by sections outlining the policy implications of the findings (Section 8.4) and recommendations for further study (Section 8.5). Finally, the thesis will be concluded in Section 8.6.

8.2 Main Findings and Key Messages

Before discussing the findings in detail, the four key messages are outlined below:

1. **Promotion of Active Travel:** The pandemic highlighted the potential for increased cycling and walking. Policies should focus on enhancing infrastructure to support these sustainable modes of transport to achieve Net Zero goals;
2. **Reduction in Peak-Hour Traffic:** The shift towards more flexible working arrangements has led to changes in commuting patterns, reducing peak travel demand and spreading traffic across the day;
3. **Socio-economic Benefits:** As well as the health benefits associated with increased active travel, the reduction in motorised traffic during the pandemic and spread of traffic in the post-pandemic may have led to decreased congestion, which can result in significant cost savings for both individuals and businesses; and
4. **The Value of Data-Driven Decision Making:** The use of cluster analysis to understand diurnal flow profiles provides valuable insights for policy-making. Investment in data collection and analysis is essential for informed decision-making and effective transport planning.

8.2.1 Holistic review of Results across the Three Studies

Prior to detailed discussion of the more specific research findings, the similarities and differences between the three studies will be discussed in this section. As cycling features in all three studies it provides the most opportunity to cross-study, however the methodology used allows for multi-modal comparison.

Firstly, there is geospatial variation in the change of cycling flow volumes across the three studies. The first study shows a decrease in city centre cycling during the lockdown on pre-pandemic levels, while the third study indicates that these flows return later in the post-pandemic era. Additionally, the two sites closest to the city centre in Study 2 experienced the largest increase in cycling post-pandemic when compared to the lockdown. This is partly explained by the fact that each of the three studies compare different periods of time, however, the combination of these results suggest that city centre locations were the most sensitive to the lockdown conditions, losing flows, only to see them return in higher numbers as things begin to return to normal. Conversely, coastal areas saw a rise in cycling both during the pandemic (Study 1) and post-pandemic (Study 3) when compared with pre-pandemic levels, which suggest they are resilient to change and is promising for future investment into routes such as the Sunrise Cycle Way in North Tyneside.

The main analysis within the studies was the cluster analysis of the diurnal flow profiles and there were differences between them when it came to choosing the optimal number of clusters; Studies 1 and 2 found that a five-cluster solution was optimal, whilst Study 3 found it to be an eight-cluster solution for both modes. This slight inconsistency is likely due to the different clustering methods used, with Ward's Hierarchical method favouring fewer, larger clusters and k-means allowing for more niche clusters to form. Within these clusters, each study produced at least one traditional AM & PM commuter shape, with the vehicle flows in Study 3 clustering into three separate commuter-shaped profiles. In terms of cycling, all studies identified an increase in these commuter shapes as lockdown eased but have not yet returned to pre-pandemic levels. Study 2 also noted a rise in pedestrian commuter shapes during the same period, as did vehicles in Study 3. This suggests a broader trend of increased commuting activity as restrictions lifted, affecting all three modes analysed.

The decrease in commuter-shaped profiles when compared to pre-pandemic levels coincides with the emergence of flatter profiles with flows spread over a wider period of the day, as was evident across all studies. Study 1 found the "Mid-day Steady" flow profile to be the most common cluster overall, which aligns with the "Flat" cycle profile observed in Study 3 during COVID, which was also the most common. Additionally, Study 1 and Study 3 showed less distinction between days of the week in their flow profiles, suggesting factors such as more flexible working has had a lasting effect on flow profiles.

8.2.2 Cycling volumes and diurnal flow profiles during COVID-19 lockdown

Over the study area, cycling flows increased on average by 30.4% during the lockdown from pre-pandemic levels. However, increases were not uniform across all 25 sites, with four of the five city centres experiencing reduced flows, whilst coastal sites doubled in flow volume and a moderate increase was found at the suburban sites.

The average volume increase across the study area is less than the 46.1% increase in miles cycled estimated by the DfT between 2020 and 2019 (DfT, 2023). Whilst miles travelled and counts are not the same measure, they are both indicative of cycling levels and one factor that is likely to have caused the difference in the study area is the higher proportion of counters within the city centre (25% of study sites) than the national average. Whilst in the post-pandemic period city centre cycling flows have increased in the post-pandemic (see Study 3), during the lockdown period covered in Study 1 these locations were associated with a decrease due to the higher prevalence of traditional commuter shape flow profiles.

The geospatial variation in cycling volumes between the city and the recreational coastal counters align with findings from other studies. Reviewing data from Streetlight (2020), Pucher & Buehler (2021) found during the pandemic, cycling volume decreased in city centres worldwide. Studying the height of lockdown (April 2020), Hong et al. (2020) found similar patterns in the UK as Pucher and Buehler (2021), where the study analysed cycle flows as the UK government-enforced policies restricted movement in the early stages of the COVID-19 pandemic in Glasgow, UK. It was found that in the early stages of the lockdown (up to April 20, 2020) cycling levels considerably increased due to non-commuting trips. Recreational cycle routes witnessed the biggest increase whilst city centres did not see a significant increase in cycling volumes, possibly attributed to restriction on commuting affecting these locations most. By studying the diurnal flow profiles across similar locations in Tyne and Wear, Study 1 was able to identify that city centres had a high prevalence of the traditional AM PM commute profiles, which was shown to also be associated with a decrease in total volume. Conversely, sites with mid-day peak flows, such as coastal sites, were associated with volume increases.

Whilst Study 1 provides an interesting insight into the response to lockdown conditions, during a time of rapid change, studying no further than the lockdown era

(August 2020) limits the relevance of the results in assessing the proceeding post-pandemic years. Study 1 concludes that further investment should stop in city centre locations. This was on account of the reduction in city centre flows with commuting diurnal profiles, supported by findings from the literature review suggesting increased WFH levels as a result of the pandemic (Bick et al., 2021; Jain et al., 2022). At the time of the pandemic, it was suggested that infrastructure investment should be focused on recreational areas such as the coast areas. However, there was a need to revisit these conclusions further into the post-pandemic period to ensure that this conclusion needed to be revised, or a ‘new-normal’ had emerged, necessitating Study 3.

8.2.3 Emergency Active Travel Fund measures and cycling and walking flows during and after the pandemic.

Overall, cycling and walking increased across the five former EATF sites. The volumes of pedestrians were substantially higher than the cyclists generally, but it was cycling that experienced proportionately the greater increase, up 40% in the post-pandemic era compared to lockdown volumes. Further examination of Argyle Street and Haldane Terrace, the sites that experienced substantial increases in active travel volumes, revealed that they are situated amongst a high concentration of students within the population. Their return to the city in the post-pandemic is likely to have been a major contributing factor to the substantial increases in flows in these areas. Nevertheless, the remaining three sites either experienced a modest growth, stayed largely the same or only decreased slightly. Whilst that does not sound convincing for meeting the active travel targets set out in the Second Cycling and Walking Investment Strategy (CWIS2), these results must be considered in the context that the wider trend at the time was of declining active travel numbers as society was emerging from the pandemic. In Great Britain, after the 46.1% increase in miles cycled during 2020 on the previous year, a decline of 21% in 2021 was followed by a further decrease 7.2% in 2022 (DfT, 2023). The fact that cycling volumes either increased or stayed similar during this period suggests that the infrastructure provided sufficient incentive to maintain volumes higher than the overall trend. Previous literature has shown that individuals, particularly inexperienced or underrepresented, value segregated infrastructure the most (Dissanayake, 2017; Steinbach et al, 2011). Cusack (2021) even found this to be more important than fear of COVID-19 transmission at the height of the pandemic when making mode choice decisions. As vehicle flows have returned to pre-pandemic volumes, segregated infrastructure will be required to restore the same level of confidence within new users that was experienced during the lockdown.

The pandemic has demonstrated that cities can rapidly expand and test active travel infrastructure investments (Dunning and Nurse, 2020). However, (Nikitas, 2021) states that there is a risk that poorly placed infrastructure could be detrimental to assisting in a modal shift to cycling. Further reading related to the EATF schemes within the case study found that reallocating the road space was not as simple as Dunning and Nurse (2020) suggests due to the need for public consultation, which often faced backlash (Holland, 2021). However, the results from this research provide evidence that reallocation of road space has a positive effect on active travel numbers and should become common practice in the 'new-normal', post-pandemic era.

8.2.4 Post-pandemic cycling flows and the emergence of a new-normal

In terms of total volumes of cycling, the biggest question is whether there has been a lasting increase (new-normal) in cycling in the post-pandemic era. Overall, in Study 3, cycling increased 17% in the study area between 2019 and 2022, much higher than the estimates from the DfT of an increase of 7.4% (DfT, 2022). Two factors could be the cause of this. Firstly, the geographical differences in the data (North East England compared with Great Britain as a whole) may be a factor. Secondly, due to the location of the inductive loop counters, the data from Study 3 mostly contains data from segregated cycle paths, whereas the DfT statistics are based on counts of on-road flows, which may have been affected differently.

The importance of analysing post-pandemic cycling flows (Study 3), rather than solely drawing conclusions at the end of the first lockdown (Study 1) was demonstrated when exploring geographic variation in flows across the study area. Study 1 revealed that whilst coastal sites experienced substantial increases in the volume of cyclists, city centres saw a decrease. However, Study 3 has shown that the city centre flows have more than recovered, experiencing higher flows in the post-pandemic study year (2022) than they were pre-pandemic (2019).

The clustering results showed morning and evening peak flow profiles were less prevalent in the post-pandemic era, with flatter profiles becoming more common and particularly noticeable on Fridays. These results suggest that the increase in cycling flows is not due only to new commuters. Whilst a proportion of these flows will be due to commuters returning to their workplace with greater flexibility, the rise in mid-day flows would suggest that there has also been a rise in non-work purpose trips. Whilst only being able to infer trip purpose with the shape of the diurnal flow profile, Section 8.5.3 will discuss how further research of a qualitative nature could complement these findings to understand the characteristics of the trips causing these shifts in diurnal flow profiles.

8.2.5 Vehicle flows in the post-pandemic era.

A review of the emerging evidence in UK transport policy suggested that vehicle flows are returning to pre-pandemic volumes, yet the time of day these were occurring may have changed. Therefore, it was decided that a greater understanding of changes in vehicle flows in addition to cycle flows, given the disproportional impact motorised vehicles have in their contribution to carbon emissions and other negative externalities (Tripp, 1942; Buchanan, 1963; Banister, 2005). The vehicle flows also act as a comparison to the cycling volumes and diurnal flow profiles in the post-pandemic.

In terms of flow volumes, the evidence across the Tyne and Wear study suggested that post-pandemic vehicle flow volumes are indeed back to pre-pandemic volumes, with a modest change of -0.06% in the mean daily flow volume. The results from the study show a closer return to pre-pandemic volumes than the national average, with road statistics from the DfT (2023) estimating a 4.4% reduction in vehicle miles travelled across Great Britain as a whole. Moreover, unlike cycling, there was little geospatial variation in the traffic volumes, with 16 of the 19 sites showing very small differences between the years. This suggests that findings during the initial lockdown period are no longer as relevant to the post-pandemic period. The study by Loo and Huang (2022) for example found that location was impacting the change in flow volume, with city centres seeing the largest reductions consistent with the cycling flows in Study 1. This highlights the urgent need to understand the long-term impact on human travel patterns (Shi et al, 2023), and not just the initial impact of COVID-19 lockdowns.

Early research suggested that after the rapid increase in WFH during the lockdown, there would be a return to the office in the post-pandemic, although not to the same extent as the pre-pandemic volumes (Bick et al., 2021; Jain et al., 2022). If commuting has indeed decreased, then there must be another trip purpose generating trips in the post-pandemic within the study area to increase traffic volumes back to the pre-pandemic levels. The literature review revealed there were signs of more enthusiasm from the population to return to in-store shopping than to their workplaces (Echaniz et al., 2021; Adibfar et al., 2022). However, the new habits in online shopping that remain (Adibfar et al., 2022), could be contributing to delivery trips; the 7.4% increase in van miles travelled across Great Britain in 2022 compared to 2019 (DfT, 2023b) suggests this may be the case.

Whilst the study of daily vehicle volumes alone shows a return to pre-pandemic conditions, the cluster analysis of the vehicle diurnal flow profiles suggest that there have been fundamental changes in the post-pandemic period that has created a *new-normal*. Similar to cycling diurnal flow profiles, the differences between weekdays and weekends are less distinguishable in terms of shape of the diurnal profile in the post-pandemic era. In addition, the traditional morning and evening peaks in commute flows are not just occurring on fewer days but typically they are not as pronounced post- compared to pre-pandemic. Finally, peaks are contributing less to the total daily volumes which are more spread over a longer time period.

It is not just temporal patterns over the day that have changed either, but also across the week. Study 3 results suggest that the diurnal flow profile with the sharpest AM and PM peak decreased in prevalence in similar proportions across all working days, approximately by a third. However, it is the shape of diurnal flow profile that replaced these flows that differ across the working week. Tuesday and Wednesday return closer to the pre-pandemic, witnessing a greater increase in the softer AM and PM peak profiles than the other working days, whilst an increase in a relatively flatter profile is seen on Thursday and Friday, previously more associated with weekends. This aligns with findings from Liu & Stern (2021), who in their study in Minnesota, USA found vehicle flows at the end of the working week (Thursday and Friday) did not recover to the same extent as the other working days after restrictions were lifted.

Gao & Levinson (2022), Loo & Huang (2022) found that the morning peak has been affected more than the evening peak. Rather than the emergence of a dual-morning peak found in Gao & Levinson (2022), the clustering results for the vehicles in Study 3 suggests that there is a trend towards later morning peaks. However, the results in

Study 3 also demonstrate changes in the working day afternoons which were noticeable, with longer, later evening peaks. The implications of these findings for transport policy and transport planning will be discussed in Section 8.4.

8.3 Interrelationship of motorised vehicle and active travel flows

One of the key findings from the literature review was that cyclists dislike riding alongside motorised traffic. Therefore, when the results of Study 3 revealed peak spreading of motorised vehicles, the reduced volume of traffic at the absolute peak might encourage more cycling. However, the results of Study 3 show that the traditional commuter-shape profile for cycling saw a greater reduction (between -42% and -64% on weekdays) than motorised vehicles (between -30% and -38% on weekdays). This could be for a number of reasons and does not mean that there are less cyclists during the peak hours than before.

As cycling volume has increased overall, it could be that on days and sites where pre-COVID only commuters were present, more types of cyclist have been added who travel at different times of day. This would explain the Cycling Cluster 1, the flat profile, which has become the most common cycle profile, increasing by 22% in the post pandemic period, especially mid-week.

Additionally, people who commute by cycling may also fit the demographic of people who can work flexibly, thus altering their commute time in the post-pandemic with the increase in hybrid working. As those who have a higher-level of education (Song et al., 2017), or have a higher income (Steinbach et al., 2011) tend to cycle more, this aligns with the findings that those who are able to work flexibly are also have a higher level of education (Bick et al., 2021; Ecke et al., 2022) and earn a higher income (Fatmi, 2020). Further research that compares pre and post pandemic volumes over the day on an hour-by-hour basis, as well as qualitative study to find out who is travelling in the middle of the day thus creating the flat profile is needed.

Conversely, the interrelationship with motorised vehicles and cycling flows on the Wearmouth Bridge site in Study 3 suggests that cyclists are more attracted to routes that avoid traffic. Cycle counts were recorded both on the road and path shared with pedestrians over the bridge. Both counts increased during lockdown, however when vehicle volumes returned in the post-pandemic, on-road cycling declined, although still remained 11% higher than pre-pandemic. On the other hand, the cycle counter on the shared path did not see a decrease after lockdown, with flows nearly doubling (99% increase) on average pre-pandemic volumes.

These results suggest that it could be newer, less-confident cyclists uncomfortable with cycling alongside traffic that contribute to the volume increase. They may have been initially attracted to cycling recreationally during lockdown when vehicle flows were low. This backs up findings from previous studies have shown that cyclists often start with recreational trips before they use it as a mode of transport for utility purposes (Song et al. 2017, cited Jones, 2012; Smith et al., 2011).

Similarly, Study 2 showed that cycling flows did not decrease immediately after lockdown at the EATF sites, whereas non-EATF sites within Study 3 did overall (see Figure 7.2). Whilst they cannot act as a direct comparison as they are independent studies, this suggests that the removal of traffic may have played a role in increasing, or at the least maintaining, the pandemic 'boom' of cycling flows. A more direct comparison between sites with and without intervention, with sufficient historical data pre-intervention (as was not available for Study 2), would increase to the understanding of the relationship between cycling and vehicle flows.

8.4 Methodological Contribution to Analysis of Diurnal Flow Profiles

The three studies have shown that clustering diurnal flow profiles can be an effective investigative tool during a time of rapidly changing conditions, as was the COVID-19 pandemic. Sections 5.7, 6.9 and 7.4 all discuss the suitability of the methodology according to their respective chapters, with the main novel methodological contributions summarised below:

1. The COVID-19 pandemic provided a novel time period to demonstrate clustering diurnal profiles can be used effectively to investigate times of uncertainty and rapid change. The method does not require the same homogenous, historical data that the time series analysis techniques which are typically adopted to forecast flows rely upon. Future studies looking at any kind of sudden disruption (either planned or not) to diurnal flow profiles will gain useful insights from their data if they follow this methodology;
2. Whilst the methodological review chapter identified studies that have used cluster analysis on data collected by bike share dock stations, another novel aspect of this research is that it is the first to demonstrate the methodology

can be applied to general cycle flows. It also uniquely analyses more than one mode at a time (Study 2 – pedestrians and cycling, Study 3 – vehicles and cycling);

3. Future studies will find much more reliable results from sites with typically higher flows, as shown by the higher silhouette coefficients in the vehicle flows when compared to the cycle flows in Study 3. A future study could identify minimal flow volumes required to obtain reasonable clustering results to improve data collection.
4. The data sets contained a much wider range of diurnal flow profiles than previous studies reviewed in Chapter 4, pushing the boundaries of what future research questions can be answered using this methodology. The intentional lack of pre-classifying diurnal flows was due to the uncertainty of what constitutes typical travel pattern for any given day in the post-pandemic era. This variation was then compiled by using very different sites, i.e. cycling counters that varied from recreational tracks to on-road city locations. However, it is still considered that normalising the flows prior to cluster analysis is essential if the main aim is to identify similarities and differences in the diurnal flow profiles.

8.5 Limitations of study

The research presented in this thesis uses data obtained within the study area of Tyne and Wear in the North East of England. Whilst the results align with the findings from other, international studies, results should be interpreted acknowledging the fact that case studies in other regions of the country and world may behave differently.

The process for handling missing data is covered for each study in each of their respective chapters. Generally, the impact of missing data is minimised by clustering data over a wider study area, 25 sites initially for Study 1 and 20 for Study 3. Whilst Study 2 possesses only five EATF sites, the alternative recording method (Machine Vision Cameras) reduced the numbers of missing data. Weijermars (2007) investigated the effect of missing data by removing 50% of the dataset, finding the results of the cluster analysis were “barely influenced” by the missing data, stating the results were not distorted. Moreover, Everitt et al. (2011) states that as cluster analysis is not an inferential technique, the existence of over-sampling some time periods, i.e. particular days of the week is acceptable.

Whilst it has been demonstrated that this methodology is able to quantify the changes in the shape of diurnal flow profiles, the causation remains unknown. A traditional daily commuting flow profile is instantly identifiable by its characteristic morning and evening peak; however, it is not possible to infer the trip purpose beyond commuting and non-commuting with flow profiles alone. Whilst the changes to lockdown restrictions provided some insight into how the trip profiles changed as different sectors re-opened, without asking a cyclist specifically the purpose of their trip it is not possible to know. However, carrying out a survey over a limited number of days would make for an interesting study into how trip purpose changes across week and non-weekdays, which will be discussed further in the future study section.

The data available can prove to be the main limiting factor when analysing long-term trends in transport. Whilst aggregating flows to hourly counts revealed patterns across the day that has allowed the discussion of results in this and the previous chapters, aggregating within a shorter time interval would reveal finer details. For example, it was not possible to assess whether the bifurcation of the morning peak observed in post-pandemic Californian cities (Gao & Levinson, 2022) had occurred in Tyne and Wear. Moreover, the lack of classified vehicle counts meant it was not possible to distinguish between cars, vans and other vehicles. Additionally, the lack of data recorded before the EATF interventions were installed in Study 2 limits the conclusions that can be drawn, this highlights the importance of a comprehensive network of counters that would ensure historical data is available if a similar study is required in the future.

8.6 Policy Implications

The review of emerging UK transport policy during the pandemic suggested that the uncertainty surrounding the pandemic remains. The National Infrastructure Strategy (NIS) stated that transport infrastructure was affected the most by COVID-19 than any other infrastructure sector (HM Treasury, 2020). Whilst society has moved into the post-pandemic era, NIS, the ‘Preparing the third Road Infrastructure Strategy 3’ document and ‘Decarbonising Transport’ all state there is a need to understand the lasting effects the pandemic has had on transport (DfT, 2021a, 2021b). The results presented in this thesis suggest that the post-pandemic era has the potential to continue to significantly impact transport policy going forward with a change in volume and shape of diurnal profiles of vehicles and cycling flows.

According to the NIS, there is a need to use road space more efficiently, citing cycling and walking alongside public transport as modes to address this issue. Furthermore, fundamental changes to commuting and business travel is significant not just because of the number of trips that they contribute to, but they also occur at the time of day when there is the greatest pressure on the network (peak hours). The results from Study 3 show that not only has there been an increase in cycling, 17% on average, but according to the cluster analysis results of vehicle flows, the times of day road space is required the most by vehicles are no longer as significant as they were pre-pandemic. These insights are complemented by those of Study 2, which demonstrated that walking and cycling volumes defied the national trend of post-pandemic decline by remaining relatively higher where road space had been reallocated to these modes. Moreover, the cluster analysis of the diurnal profiles show that individuals are not only using these for recreational purposes but have adapted to the new provision for commuting purposes. This provides evidence to local authorities that despite the public backlash by a minority (Holland, 2021), reallocation of road space to active modes have proved popular for users and an effective way to contribute to net zero targets whilst removing the other localised negative externalities associated with vehicle traffic.

Whilst road traffic statistics suggest cycling volumes remain 7.4% higher in 2022 than 2019 (DfT, 2023b), Study 3 showed this number was even higher at 17% during the same time period across the counters within the Tyne and Wear study area. These increased cycling levels witnessed during the pandemic offers an opportunity to align recovery policies with the transition to net zero (Marsden & Docherty, 2021).

However, the CWIS2 aims are even more ambitious, to double cycling trips from 2018 levels by 2025. These results show that whilst there have been substantial increases across the study period between 2019 and 2022 levels, there is still some way to go. Study 2 demonstrated that in locations where road space had been reallocated to active travel, there had not been the same decrease in flows immediately after the lockdown as experienced generally. The findings from this thesis suggest that even with the upheaval of the pandemic and unprecedented rise of cycling during the pandemic, national government and local authorities will have to be proactive, and providing more segregated infrastructure is a solution.

8.7 Future study

Recommendations for future study fall into two broad categories. Firstly, studies that use the same methodology; including repeating the study in a different location, collecting data further into the post-pandemic period (2023 onwards), or a deeper analysis of an individual site of interest. Alternatively, further study should aim to understand *what* is causing the change in diurnal flow profiles through qualitative research methods.

8.7.1 Study of New Low Traffic Neighbourhoods.

Despite all transport policy suggesting that Low Traffic Neighbourhoods (LTN) are an effective way to encourage sustainable transport whilst bringing all the health benefits and improvements of the urban environment, the UK Government has since backpedalled, suggesting they should be halted in 'the plan for drivers' published October 2023 (DfT, 2023c). Therefore, research into the effectiveness of encouraging sustainable transport using LTNs has never been more crucial. Whilst Study 2 in this thesis demonstrated that they are an effective way of encouraging more and different types of cycling trips, it would be valuable to add further locations, investigating the post-pandemic period to reduce the effect caused by the short-term populations as experienced in Study 2.

With this in mind effort was made to source data from another city to compare with Newcastle. Following an exchange of emails, a meeting was held with a Transport Planner at Oxfordshire County Council (OCC) on the 26th of April 2022. Unfortunately, an agreement could not be struck as to what would be studied. OCC stated there would be "*some caveats about the divisive nature of the LTNs in which the dissemination of results may need to be mindful of*". Whilst understandable from a political point of view, this fundamentally does not meet the criteria for unbiased scientific research.

What would be needed for a like-for-like comparison with Newcastle was not possible, due to the sensitivity of the data given the controversy of such schemes, and Oxford's schemes had not yet been made permanent as in Newcastle. The data that OCC was willing to share and the aims and objectives they had in mind for the research would not have provided any meaningful comparison and therefore it was mutually decided not to pursue the study. In light of the growing use of LTNs as a political weapon, it is extremely unlikely that Local Authorities will share this data in the future. If this is the case, it is recommended that future researchers interested in LTNs revisit Strava data. Larger, busier study areas than the five sites in Study 2 should not experience the same issue with low counts highlighted in Chapter 6.

8.7.2 Complementing Results with Qualitative Data

The literature review revealed that the decision to cycle is complex and has many factors ranging from socio-demographics to the surrounding physical environment. Moreover, the importance of the latter can be influenced by the former. It has been suggested that for cycling, using qualitative methods can help understand better the behaviour associated with cycling (Walta, 2018). Now that the pandemic is behind us and there is no risk associated with planning research that requires in-person interviews, it is proposed that a worthwhile study would be to survey cyclists, for example, to compare the trips occurring at coastal and city centre sites. The following research topics could then be studied:

1. Using loop detectors, the trip purpose is something that can only be inferred by the time of day and day of week and location at which trips are occurring. This could be confirmed by surveying cyclists throughout the day across the week;
2. Cyclists could be asked how much they cycled before, during and currently (after) the pandemic, and the reasons for change if they were different;
3. Socio-demographics would be valuable to understand whether the same underrepresentation of some groups of society who cycle remains in the post-pandemic.

8.8 Conclusion

The findings from this research suggest that the increase in cycling flows combined with fundamental changes in the diurnal flow profiles of vehicle traffic in the post-pandemic will have a significant impact on addressing net zero targets. The reduction in peak time vehicle flows presents a stronger case for the reallocation of road space to sustainable modes such as cycling. This would be achieved by creating segregated infrastructure and planning LTNs. The key message from the literature review is that these are necessary measures to stand any chance of meeting the CWIS2 target to double 2018 cycling trips by 2025 and the results from Study 2 support their implementation. Without action, this additional capacity could soon be filled with induced travel demand as the economy recovers post-COVID and the population increases.

According to the Net Zero Strategy, the UK is at a “crossroads in history” moving on from the pandemic, it will not be sustainable to return to pre-pandemic habits. Picking up this crossroads metaphor, the results presented in this thesis suggest that whilst the transport sector momentarily slowed in anticipation of a change in direction, it has not yet indicated to turn off the main road at the unexpected junction the COVID-19 pandemic presented, and time is running out to do so.

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Appendices

Appendix A. R Code for Cluster Analysis

Tasks prior to running R code:

1. Install required packages:

```
library(cluster)
library(factoextra)
library(scales)    ### to force axis to be full numbers and not scientific shorthand
library(gridExtra) ###plotting graphs in one figure
library(ggplot2)
library(reshape2) ### melting columns together
library(dplyr) ### filtering categorical variables (removing bad clusters)
```

2. Import time series data.

For example using ‘Import Dataset > From Excel…’ feature. Time series should be in the structure of 24 columns of hourly counts, and each row representing an individual diurnal flow profile (i.e., one day at one site). Rename the new dataframe “flows” as has been done in the first line of section A.1 of this Appendix and run the subsequent script.

A.1 Hierarchical Clustering (Study 2)

```
flows <- TRB_cycling_normalised_only [7:30]
euc.dist <- dist(flows, method = "euclidean")


`rownames<-`(flows,TRB_cycling_normalised_only$ID)
flows


rownames(TRB_cycling_normalised_only) <- TRB_cycling_normalised_only$ID



alt_5C_cyc <- hcut(euc.dist, k=5, hc_method = "ward.D2")

fviz_cluster(alt_5C_cyc,geom = "point", ellipse.type = "norm", main = "Cyclists", ggtheme =
theme_bw())


plot(alt_5C_cyc, labels = FALSE,)
```

```
v2_5C_cyc <- hcut (flows, k=5, hc_method = "ward.D2", hc_metric = "euclidean", graph = TRUE)


fviz_cluster(v2_5C_cyc,geom = c("point"), ellipse.type = "norm", main = "Cyclists", ggtheme =
theme_bw())

v2_5C_cyc <- hcut (flows, k=5, hc_method = "ward.D2", hc_metric = "euclidean", graph = TRUE)

fviz_dend(v2_5C_cyc, show_labels = FALSE)
```

A.2 Comparing K-means and Hierarchical Clustering (Study 3)

```
flows <- vehicles_2019[42:65]


####plotting hierarchical and kmeans####


###WSS###

km.wss <- fviz_nbclust(flows, kmeans, method = "wss", k.max = 15)
hc.wss <- fviz_nbclust(flows, hcut,method = "wss", k.max = 15)


km.wss.line <- km.wss[["data"]]
hc.wss.line <- hc.wss[["data"]]

wss.combine <- cbind(km.wss.line,hc.wss.line[2])
colnames(wss.combine) <- c("Clusters","Kmeans","Hierarchical")

wss.combine


wss.kmvshcplot <- ggplot(wss.combine, aes(Clusters, Hierarchical, group = 1))+
  geom_point(data = wss.combine,mapping = aes(x = Clusters,y = Hierarchical), color="blue")+
  geom_point(data = wss.combine,mapping = aes(x = Clusters,y = Kmeans), color="red")+
  geom_line(data = wss.combine,mapping = aes(x = Clusters,y = Kmeans),color="red")+
  geom_line(data = wss.combine,mapping = aes(x = Clusters,y = Hierarchical),color="blue")+
  theme_bw()+
  labs(x="No. of Clusters",y="Within Sum of Squares",title="Within Sum of Squares Plot")

wss.kmvshcplot


### SILHOUETTE ###

km.sil <- fviz_nbclust(flows, kmeans, method = "sil", k.max = 15)
hc.sil <- fviz_nbclust(flows, hcut,method = "sil", k.max = 15)


km.sil.line <- km.sil[["data"]]
hc.sil.line <- hc.sil[["data"]]

sil.combine <- cbind(km.sil.line,hc.sil.line[2])
colnames(sil.combine) <- c("Clusters","Kmeans","Hierarchical")

sil.combine


sil.kmvshcplot <- ggplot(sil.combine, aes(Clusters, Hierarchical, group = 1))+
  geom_point(data = sil.combine,mapping = aes(x = Clusters,y = Hierarchical), color="blue")+
  geom_point(data = sil.combine,mapping = aes(x = Clusters,y = Kmeans), color="red")+
```

```
  geom_line(data = sil.combine,mapping = aes(x = Clusters,y = Kmeans),color="red")+
  geom_line(data = sil.combine,mapping = aes(x = Clusters,y = Hierarchical),color="blue")+
  theme_bw()+
  labs(x="No. of Clusters",y="Av. Silhouette Width",title="Silhouette Plot")

sil.kmvshcplot



### GAP STAT PLOT ###

km.gap <- fviz_nbclust(flows, kmeans, method = "gap_stat", k.max = 15, nboot = 5)
hc.gap <- fviz_nbclust(flows, hcut,method = "gap_stat", k.max = 15, nboot = 5)


km.gap.line <- km.gap$data$gap
hc.gap.line <- hc.gap$data$gap

gap.combine <- cbind(km.sil.line[1],km.gap.line,hc.gap.line)
colnames(gap.combine) <- c("Clusters","Kmeans","Hierarchical")

gap.combine


gap.kmvshcplot <- ggplot(gap.combine, aes(Clusters, Hierarchical, group = 1))+
  geom_point(data = gap.combine,mapping = aes(x = Clusters,y = Hierarchical), color="blue")+
  geom_point(data = gap.combine,mapping = aes(x = Clusters,y = Kmeans), color="red")+
  geom_line(data = gap.combine,mapping = aes(x = Clusters,y = Kmeans),color="red")+
  geom_line(data = gap.combine,mapping = aes(x = Clusters,y = Hierarchical),color="blue")+
  theme_bw()+
  labs(x="No. of Clusters",y="Gap Statistic",title="Gap Statistic Plot")

gap.kmvshcplot


###plotting wss, silhouette and gap on top of eachother ###


grid.arrange(wss.kmvshcplot, sil.kmvshcplot,gap.kmvshcplot,nrow=3, top="2019 Cycling Flows")
```

A.3 K-means Clustering (Study 3)

```
#### assigning clusters to dataset ####

set.seed(123)

km.cyc <- kmeans(flows,8)

km.cyc

###silhouette graphic ###

sil.cyc <- silhouette(km.cyc$cluster, dist(flows)) #needed to extract cluster membership in correct order

head(sil.cyc)

silplot.cyc <- fviz_silhouette(sil.cyc)

silplot.cyc


#### assigning cluster membership, neighbour and sil width to dataset ####

output <- cbind(cycle_over_3_top_20_sites , sil.cyc)

write.csv(output, file = "cyc_over_3_av_flow_8C.csv")




"Cluster.Number" = c("C1","C2","C3","C4", "C5", "C6","C7", "C8")

summaryt_cyc <- cbind(Cluster.Number,silplot.cyc[["plot_env"]][["ave"]],
km.cyc$withinss,km.cyc$size)

summaryt_cyc <-`colnames<-`(summaryt_cyc,c("Cluster Number", "Av. Silhouette Width","WSS",
"Size"))

###convert from 'atomic vector' and Size column to become a numeric variable rather than
character ###

summaryt_cyc <- as.data.frame(summaryt_cyc)

summaryt_cyc$Size <- as.numeric(summaryt_cyc$Size)

summaryt_cyc

write.csv(summaryt_cyc, file = "minitable_cyc_20s.csv")


####PART 2 - Plotting Av Cluster Profiles####

###retrieving data from kmeans###
```

```
profile.plot.cyc <- km.cyc$centers

profile.plot.cyc

###transposing###

tr.prof.plot.cyc <- t(profile.plot.cyc)

tr.prof.plot.cyc

### merging columns ###

tr.prof.plot.cyc.melt <- melt(tr.prof.plot.cyc)

colnames(tr.prof.plot.cyc.melt) <- c("Hour", "Cluster", "Normalised_Flow")

tr.prof.plot.cyc.melt$Cluster <- as.factor(tr.prof.plot.cyc.melt$Cluster) ##turn cluster ID from
numeric to categorical value

melt.cyc <- tr.prof.plot.cyc.melt


plot_cyc <- ggplot(melt.cyc, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = melt.cyc,mapping = aes(x = Hour,y = Normalised_Flow, color= Cluster))+
  scale_fill_brewer(palette = "Set1")+
  geom_line(data = melt.cyc,mapping = aes(x = Hour,y = Normalised_Flow, color= Cluster))+
  scale_fill_brewer(palette = "Set1")+
  theme_bw()+
  scale_fill_brewer(palette = "Set1")
theme(legend.position = c(.9,.7))+

  labs(x= "Hour of Day", y= "Normalised Flow", title = "cyc")

plot_cyc


###filter###

filter1.cyc <- filter(melt.cyc, Cluster != 4, Cluster != 5)


filter1_cyc_plot <- ggplot(filter1.cyc, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = filter1.cyc,mapping = aes(x = Hour,y = Normalised_Flow, color= Cluster))+
  scale_fill_brewer(palette = "Set1")+
  geom_line(data = filter1.cyc,mapping = aes(x = Hour,y = Normalised_Flow, color= Cluster))+
  scale_fill_brewer(palette = "Set1")+
  theme_bw()+

  labs(x= "Hour of Day", y= "Normalised Flow", title = "Filtered Cycling Profiles")


filter1_cyc_plot




##plot individual, e.g. Cluster 1.
```

```
Cluster1.df <- filter(melt.cyc, Cluster == 1)

Cluster1.df

cl1_plot <- ggplot(Cluster1.df, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = Cluster1.df,mapping = aes(x = Hour,y = Normalised_Flow,))+
  geom_line(data = Cluster1.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  theme_bw()+
  geom_hline(yintercept = 0, linetype= 2)+
  labs(x= "Hour of Day", y= "Normalised Flow", title = "Cluster 1")

cl1_plot

###Cluster 2###
Cluster2.df <- filter(melt.cyc, Cluster == 2)

Cluster2.df

cl2_plot <- ggplot(Cluster2.df, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = Cluster2.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  geom_line(data = Cluster2.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  theme_bw()+
  geom_hline(yintercept = 0, linetype= 2)+
  labs(x= "Hour of Day", y= "Normalised Flow", title = "Cluster 2")

###Cluster 3###
Cluster3.df <- filter(melt.cyc, Cluster == 3)

Cluster3.df

cl3_plot <- ggplot(Cluster3.df, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = Cluster3.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  geom_line(data = Cluster3.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  theme_bw()+
  geom_hline(yintercept = 0, linetype= 2)+
  labs(x= "Hour of Day", y= "Normalised Flow", title = "Cluster 3")

###Cluster 4###
Cluster4.df <- filter(melt.cyc, Cluster == 4)

Cluster4.df

cl4_plot <- ggplot(Cluster4.df, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = Cluster4.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  geom_line(data = Cluster4.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  theme_bw()+
  geom_hline(yintercept = 0, linetype= 2)+
  labs(x= "Hour of Day", y= "Normalised Flow", title = "Cluster 4")


###Cluster 5###
Cluster5.df <- filter(melt.cyc, Cluster == 5)

Cluster5.df

cl5_plot <- ggplot(Cluster5.df, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
```

```
  geom_point(data = Cluster5.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  geom_line(data = Cluster5.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  theme_bw()+
  geom_hline(yintercept = 0, linetype= 2)+
  labs(x= "Hour of Day", y= "Normalised Flow", title = "Cluster 5")

###Cluster 6###
Cluster6.df <- filter(melt.cyc, Cluster == 6)

Cluster6.df

cl6_plot <- ggplot(Cluster6.df, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = Cluster6.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  geom_line(data = Cluster6.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  theme_bw()+
  geom_hline(yintercept = 0, linetype= 2)+
  labs(x= "Hour of Day", y= "Normalised Flow", title = "Cluster 6")

###Cluster 7###
Cluster7.df <- filter(melt.cyc, Cluster == 7)

Cluster7.df

cl7_plot <- ggplot(Cluster7.df, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = Cluster7.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  geom_line(data = Cluster7.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  theme_bw()+
  geom_hline(yintercept = 0, linetype= 2)+
  labs(x= "Hour of Day", y= "Normalised Flow", title = "Cluster 7")

###Cluster 8###
Cluster8.df <- filter(melt.cyc, Cluster == 8)

Cluster8.df

cl8_plot <- ggplot(Cluster8.df, mapping = aes(x=Hour, y=Normalised_Flow, group= Cluster))+
  geom_point(data = Cluster8.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  geom_line(data = Cluster8.df,mapping = aes(x = Hour,y = Normalised_Flow))+
  theme_bw()+
  geom_hline(yintercept = 0, linetype= 2)+
  labs(x= "Hour of Day", y= "Normalised Flow", title = "Cluster 8")

grid.arrange(silplot.cyc,
          grid.arrange(cl1_plot,cl2_plot,cl3_plot,cl4_plot,cl5_plot,cl6_plot,cl7_plot,cl8_plot,
nrow=2, top= "Cycling Cluster Profiles"), nrow=2)




grid.arrange(cl1_plot,cl2_plot,cl3_plot,cl4_plot,cl5_plot,cl6_plot,cl7_plot,cl8_plot, nrow=2, top=
"Cycling Cluster Profiles")
```

Appendix B. Additional Figures from Study 3

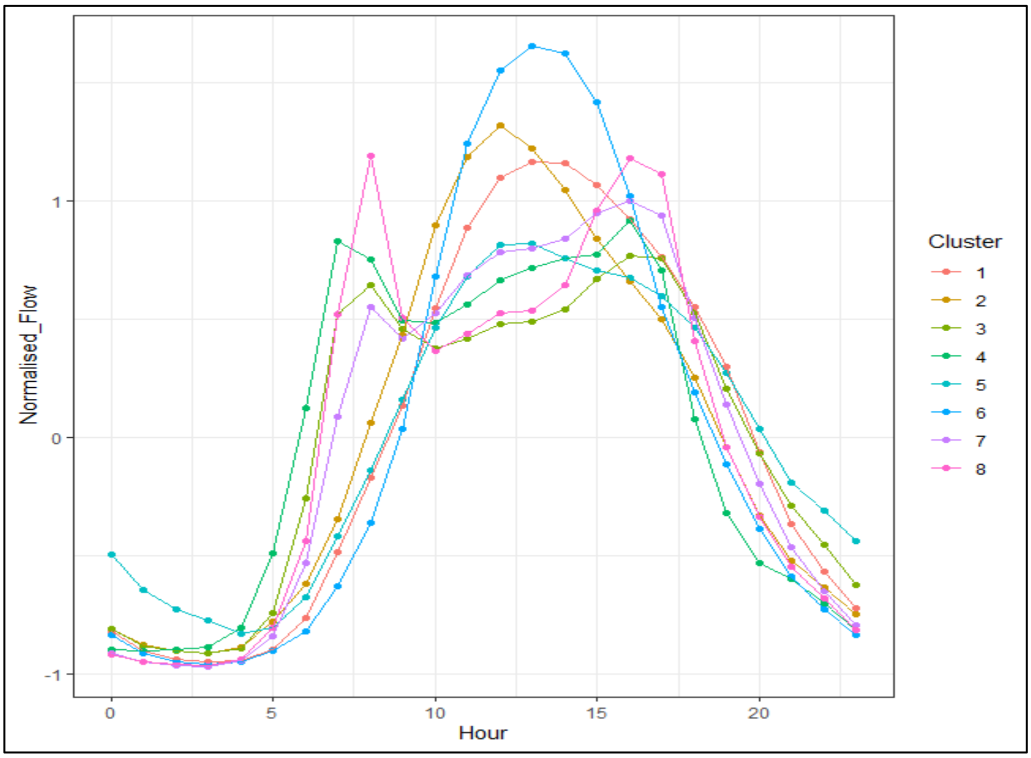

Figure B.1. Average profiles of each cluster (vehicles)

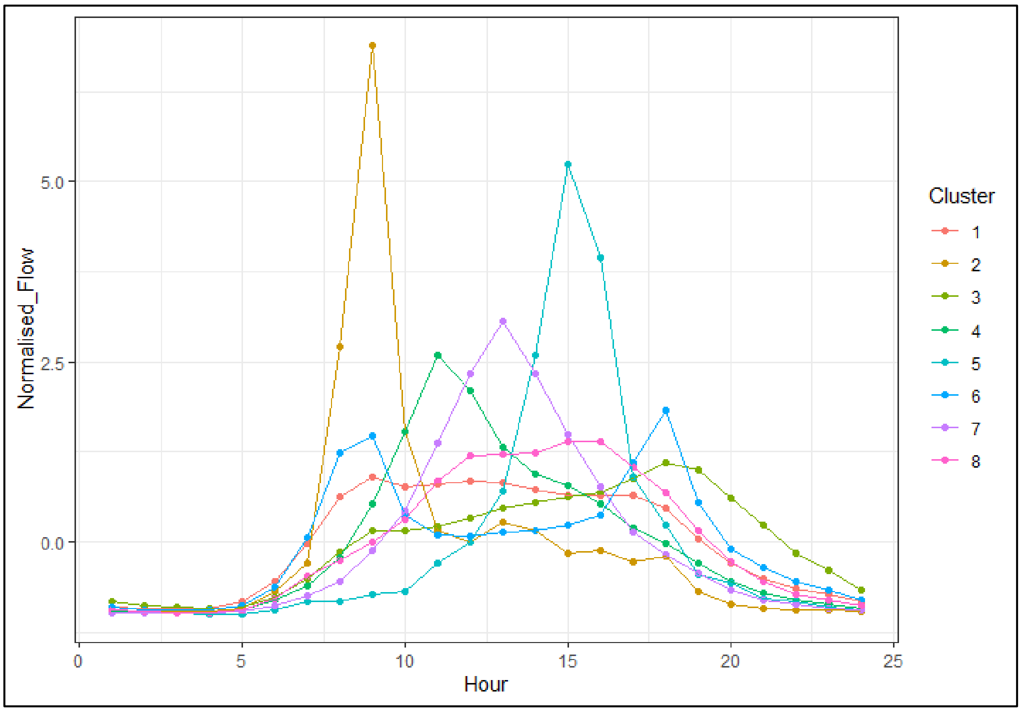

Figure B.2 Average cluster profiles (cycling)

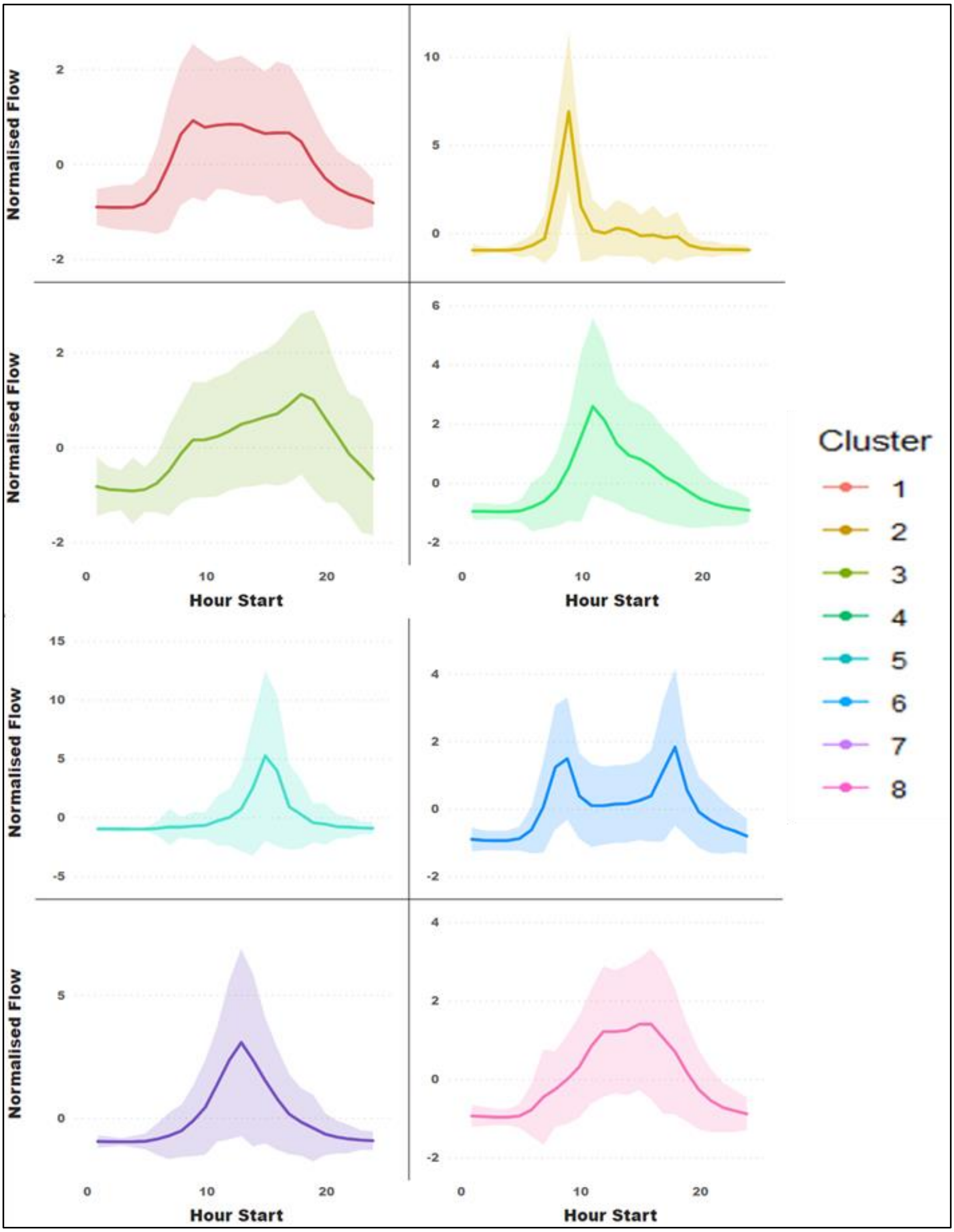

Figure B.3 Av. Cycle Cluster Profiles to two Standard Deviations

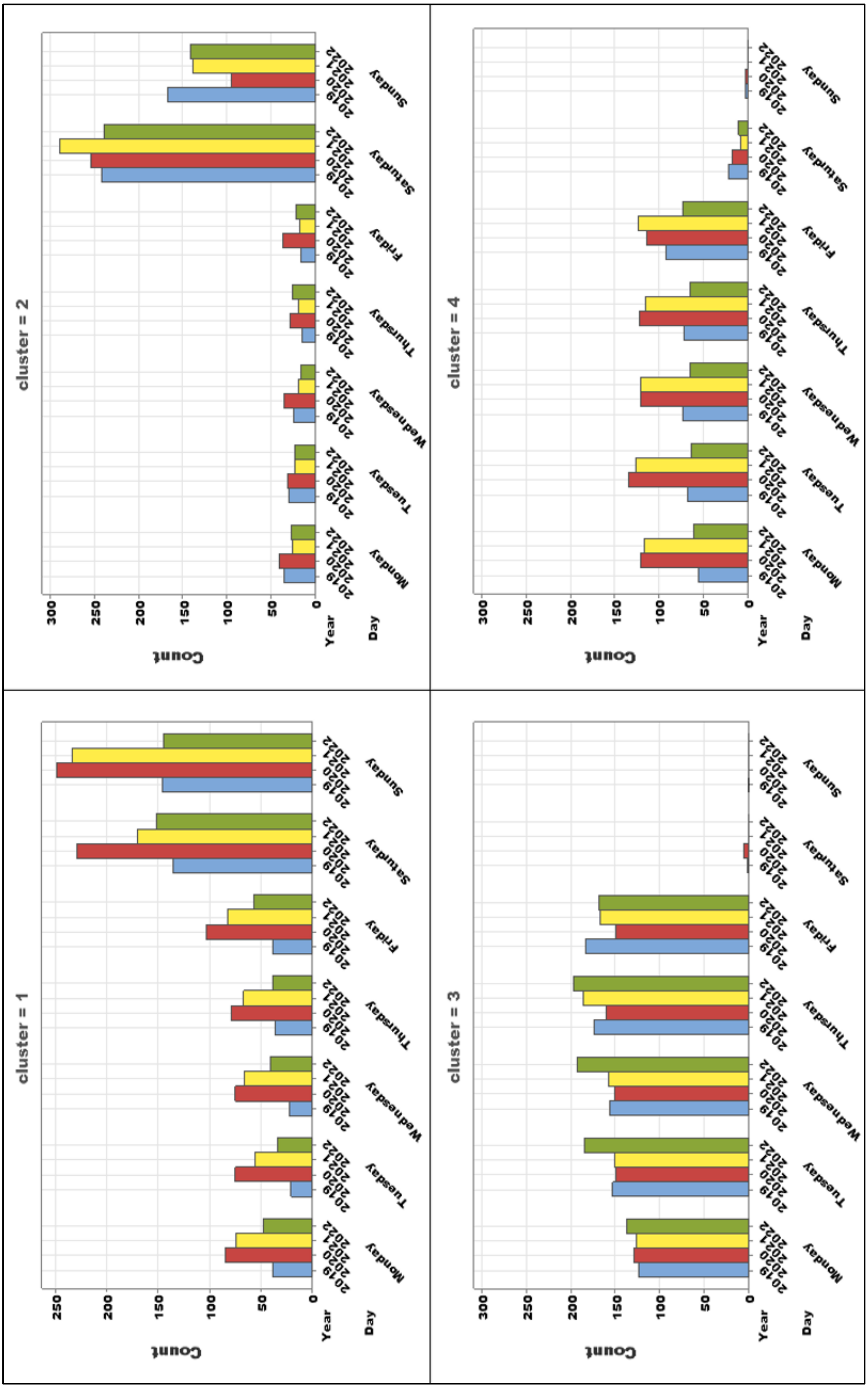

Figure B.4. Clusters 1-4 Frequency by Day by Year (Vehicles)

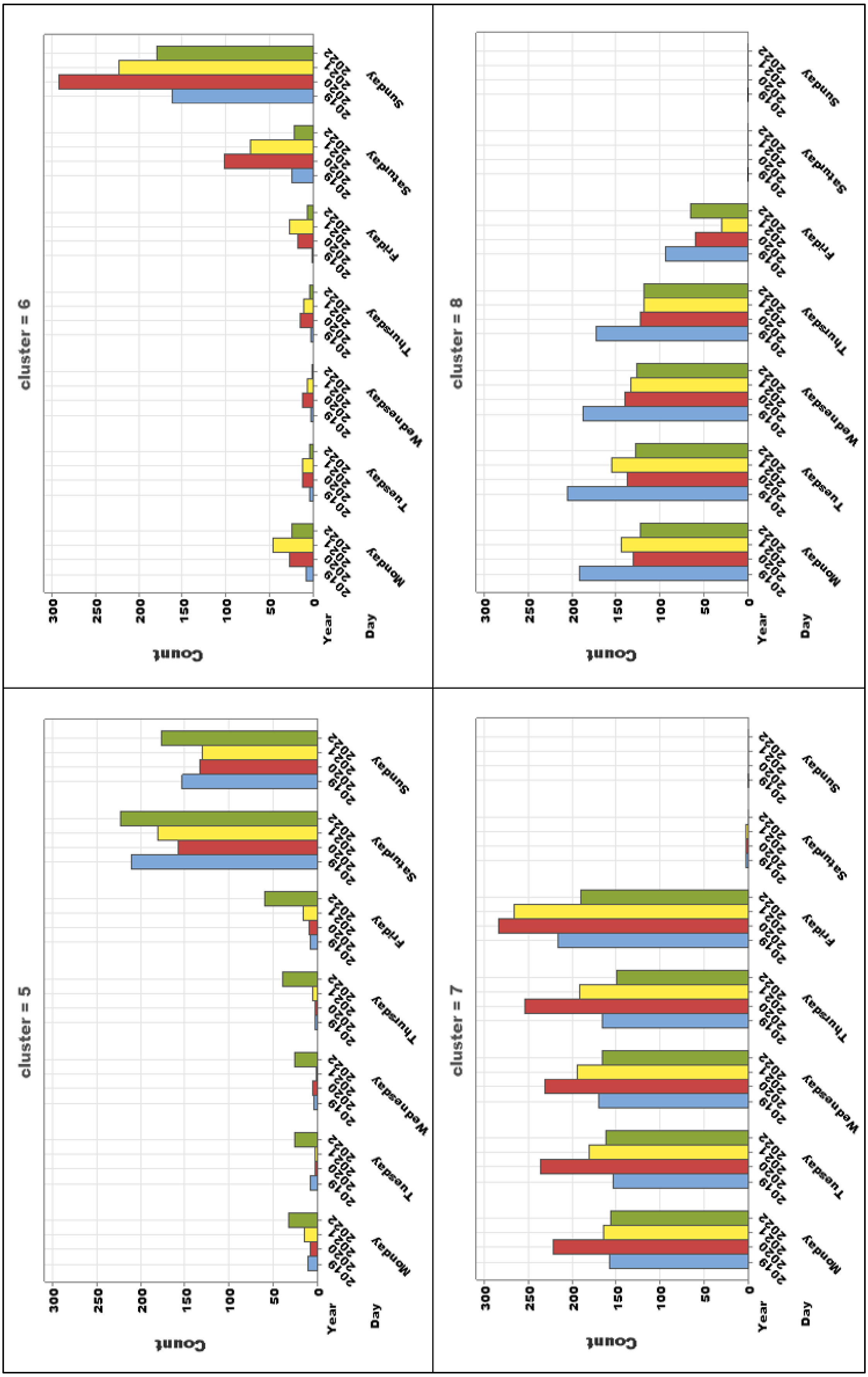

Figure B.5. Clusters 5-8 Frequency by Day by Year (Vehicles)

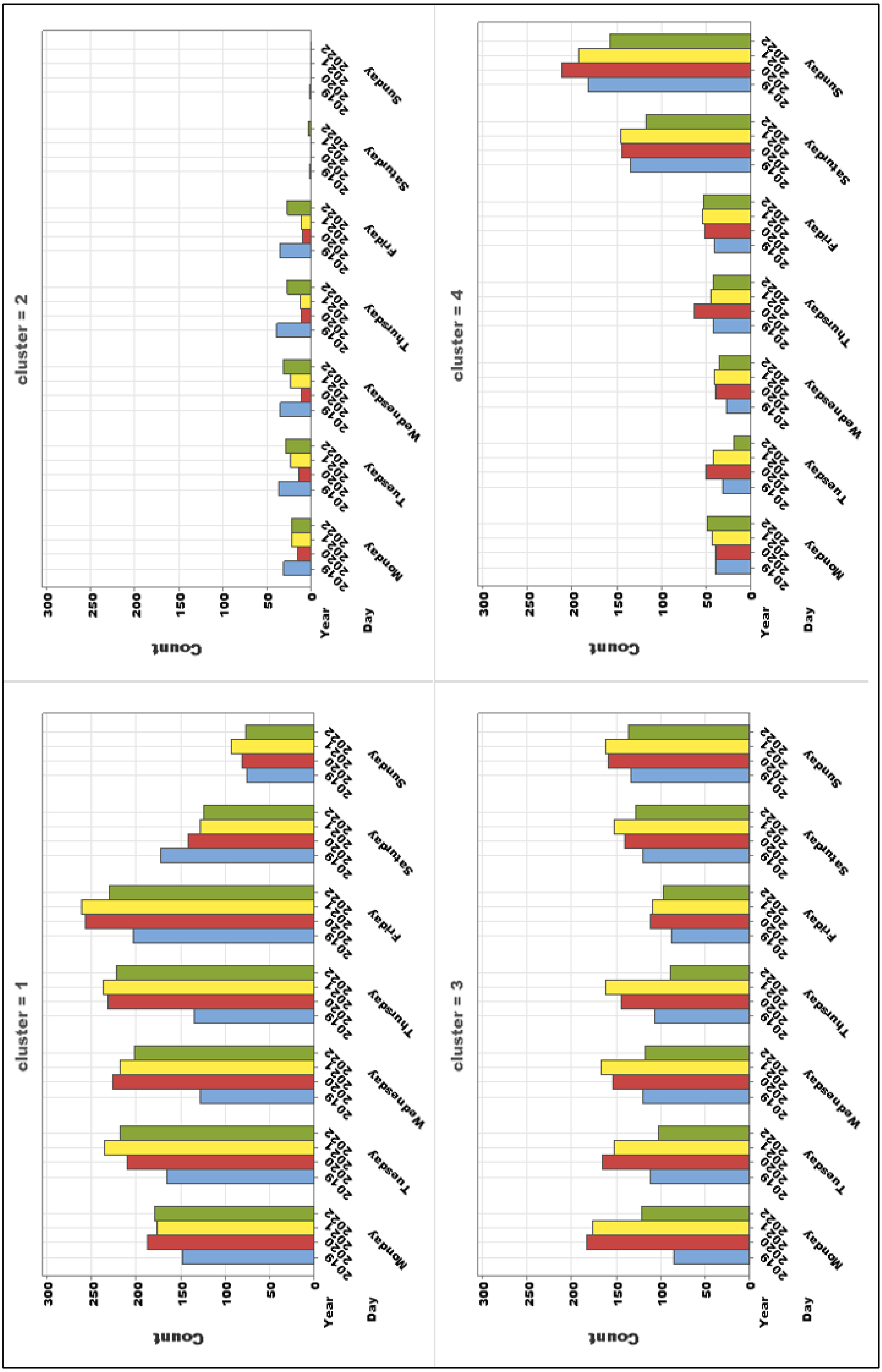

Figure B.6. Clusters 1-4 Frequency by Day by Year (Cycles)

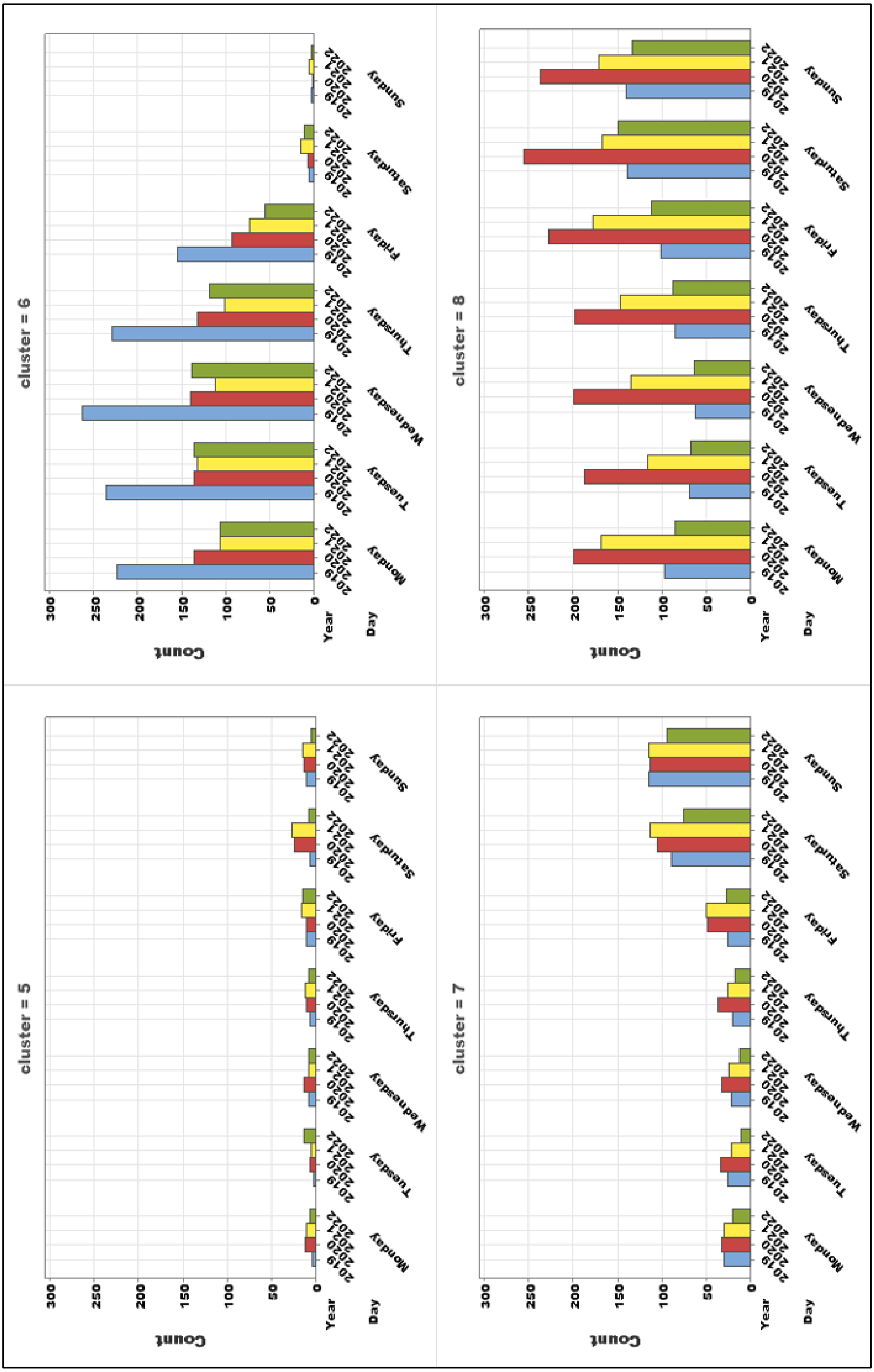

Figure B.7 Clusters 5-8 Frequency by Day by Year (Cycles)