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Research Article

Cluster Analysis of Daily Cycling Flow Profiles during COVID-19 Lockdown in the UK

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The COVID-19 pandemic and resulting government-enforced lockdown affected the travel behavior and lives of people worldwide. In this research, hierarchical cluster analysis (HCA) is used to quantify the impact on daily flow profiles of cyclists due to the public's response to different levels of restrictions during a 6-month period of the COVID-19 pandemic in 2020. An inductive loop network in Tyne and Wear, the UK provided cycle flow data from 25 sites. A paired sample t-test was carried out between the "Pre-COVID-19" baseline year and 2020 to determine how cycling volumes changed at each site. The HCA was then performed on the diurnal hourly flow profiles to observe how they changed within the same time period. Finally, the relationship between diurnal flow profile and volume was assessed. Overall cycling volume in the study area increased by 38% during the lockdown. The highest increases were found at coastal sites, with more modest increases in suburban areas and reduced volumes at city center locations. The HCA of the diurnal flow profiles revealed that locations associated with noncommuting-shaped flows witnessed the largest increases while commuting profiles saw a decrease. As lockdown restrictions eased, flow profiles began to revert back to the prepandemic norm but never fully returned to prepandemic levels. The adoption of working from home postpandemic will change commuting behavior. The conclusions drawn from this study suggest consideration of noncommuting trips should be made when planning the design and location of future cycling schemes, and the HCA of flow profiles can assist in this decision-making process as a method to quantify changes in daily flow profiles of cycling.

1. Introduction

Despite eagerness for society to return to normal following the COVID-19 pandemic, there is a growing consensus that what existed before was not sustainable given the global environmental issues. This has resulted in calls to "build back better" through investment in a green recovery plan [1]. Climate change existed before COVID-19 and will persist without action. Nations across the world have pledged net zero greenhouse gas emissions by 2050 as part of the Paris agreement in 2015. Countries are being urged to come forward with more ambitious reductions by 2030. The UK has already committed to a reduction of 68% of 1990 levels by 2030 and 78% by 2035 [2]. Active travel modes such as walking and cycling remain a strong solution to removing carbon emissions from our transport network while providing a host of other benefits such as to health, improved urban environment, and social inclusivity.

Prior to the COVID-19 pandemic, the UK was expected to fail to achieve the target set out in the Walking and Cycling Investment Strategy 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" [3, 4]. This can be attributed to many 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 motorized vehicles, will reduce the chance of re-election due to their controversy [5]. Additionally, those that are less confident or feel under-represented within the cycling community including women, disabled people, and ethnic minority groups need greater support and encouragement to switch to cycling [6, 7] and have been shown to prefer more segregation from cars, which must be accounted for in the analysis of cycle design preferences [8]. Similarly, the level of confidence of the cyclist [9] and the purpose of the journey [10] also influence infrastructure preference. Such issues as these must be addressed in order to increase cycling numbers, promote a green recovery, and thus work toward net zero along with achieving a fairer society. Providing as many tools and evidence as possible to decision-makers faced with delivering schemes to increase cycling will facilitate this.

Amid the global COVID-19 pandemic, the UK government announced its first lockdown on March 26, 2020, with a ban on nonessential travel. The general public had already been advised to work from home (WFH) if possible, but the lockdown meant that schools, pubs, restaurants, and nonessential retail among others closed. It was not until the 11th of May that people were encouraged to return to work. Schools began to reopen on the 1st of June, and pubs and restaurants were allowed to open under restricted conditions on the 4th of July. The easing of restrictions was short-lived because throughout the second half of 2020, there were localized lockdowns, which culminated in a full national lockdown at the end of 2020. This was gradually eased between March 8, 2021, and June 21, 2021. However, on December 13, 2021, the UK government reinstated the advice to WFH if possible due to the spread of the COVID-19 Omicron variant. It may be some time before society is completely free from COVID-19 restrictions.

The initial lockdown of society resulted in a substantial fall in motorized traffic to a volume that was incomprehensible at the start of 2020. During April, the month with the most severe bans on travel, road traffic was 63% lower than during April 2019 [11]. At the same time, there were "unprecedented levels of walking and cycling" [12] as cycling during the COVID-19 pandemic became a much more popular choice of mode across the UK [13, 14] and in other parts of the world [15–17]. Moreover, the shift in office culture toward WFH and flexible working, which had begun prior to the pandemic, has been accelerated because of lockdown restrictions. Its prevalence in postpandemic and its effect on travel demand, particularly the daily commute, are not yet clear. Developing a methodology to analyze and quantify the shift and investigating the characteristics of cycle trips, in terms of location (geospatial) and time of day (temporal), deepens the understanding of the demand for cycling. Also, the methodology is useful to monitor the changes as society begins to move on from the pandemic.

Therefore, the aim of this study is to analyze the influence of geospatial and temporal factors on the changing volumes of cycle trips during the COVID-19 pandemic. This will be achieved by completing the five objectives as follows:

(1) To capture cycle flow data from detectors over a pre-COVID-19 period, compare it to volumes during the COVID-19 lockdown, and process and manipulate it into formats for the analysis,

(2) To perform a high-level analysis to establish the statistical significance of the weekly changes in cycle flows across the region during COVID-19 compared with pre-COVID-19,

(3) To carry out a more advanced and in-depth analytical analysis to cluster the diurnal hourly cycle flows to understand the changes in the daily flow profile of cycle trips before and during COVID-19,

(4) To explore whether the magnitude of the changes in cycle volumes before and during COVID-19 is related to the prevalence of certain flow profiles at a given counter, and

(5) To integrate the outputs to investigate the implications for policy.

Upon completing these five objectives, this study makes an original contribution by presenting:

(1) A methodological approach for performing cluster analysis on unclassified diurnal cycle flow profiles across a network;

(2) A procedure to determine relationships between diurnal cycle flow profiles and total flow volumes; and

(3) The application of the procedure to cycle flow profiles for analyzing the effect of the COVID-19 pandemic on flow volumes.

1.1. Review of Literature Related to Cycling during COVID-19 Pandemic. Nikitas et al. [18] provide an extensive review of the lessons learnt during the pandemic with regard to cycling. It is identified that the pandemic has highlighted problems with a car-centric urban environment inhibiting active transportation. Research into road user views suggests that cycling levels after the pandemic will remain higher than they were before. While some were hugely successful, other temporary cycle infrastructure introduced during the pandemic failed and was heavily criticized. One reason cited was its inability to appeal to the majority of users of the infrastructure (e.g., commuters, retail, and recreational). Dunning and Nurse [19] 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 motorized vehicles to cycles on already constructed roads. They state what is less clear is whether these interventions have occurred in the right places. While one key strength of temporary infrastructure is that it can be modified or removed, Dunning and Nurse agree with Nikitas et al. that poor experimentation may result in a negative reaction in terms of both behavior and attitudes toward future cycling infrastructure, as has been identified with schemes that predate the pandemic [5]. Planning new cycle infrastructure postpandemic will remain a "complex process" [18], 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 (number of cycles measured depending on each hour of the day) reflects the trip purpose—whether they are mostly commuting or noncommuting.

Hong et al. [14] go some way to address this uncertainty. Cycle volumes were analyzed from Strava data as the UK government-enforced policies restricting movement in the early stages of the COVID-19 pandemic in Glasgow, UK. The study found that in the early stages of the lockdown (up to April 20, 2020) cycling levels considerably increased due to noncommuting trips. Infrastructure type also influenced cycling volume. Interestingly, it was recreational cycle routes that were already segregated from traffic that saw 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 center-segregated infrastructure, which was a focus of policy pre-COVID-19, did not see a significant increase in cycling volumes, possibly attributed to restriction on commuting affecting these locations most. This suggests that the prevalence of commuting and noncommuting flows had a significant effect on the volumes of cyclists using a specific route during the pandemic. Given that the times of the day most people commute as opposed to shop or engage in leisure activity, studying the total flows over the day is rather limiting. Further research is required to explore whether similar or different responses are spatially and temporally found over the day and how these changes differ beyond the first lockdown of 2020 as different levels of restriction were introduced.

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. [20] suggest that COVID-19 has helped strengthen the social narrative that cycling is healthy not only just 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. [21] 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 above states the importance of maintaining the increased cycling levels 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 the academic literature and popular press [22, 23]. The research presented in this study demonstrates how data clustering, an underutilized analysis tool in cycle flow analysis, can be such a resource given that it is highly transferable to any location and scenario. By using this methodology, additional detail within the daily flows, such as the prevalence of commuting in the morning and evening and noncommuting trips, which take place at different times of the day, can be revealed that would otherwise be lost in total daily flow counts. The methodology will be demonstrated by comparing cycle flows before and during the UK lockdown and restricted periods across Tyne and Wear, a metropolitan region in the northeast of England.

1.2. Review of Previous Research Using Clustering of Traffic Flow Profiles. There is a robust body of research on daily flow profiles of motorized traffic prior to the COVID-19 pandemic, which informs better policy decisions such as public transport provision, congestion zone timings, and improving transport models. Crawford et al. [24] explain that some of these models treat day-to-day fluctuations in flow profiles as random; however, models will be improved by predicting, to some degree, flows based on factors such as the day of the week, season, or a specific bank holiday. The choice of clustering approach is a vital aspect of traffic data mining. There are various clustering algorithms, including Bayesian, hierarchical, and K-means. Among them, hierarchical clustering has been used by researchers in the past for analyzing traffic flows [25, 26].

Weijermars and van Berkum [25]'s study is an example of a study that uses hierarchical cluster analysis to analyze preclassified flow patterns to better predict traffic flows for testing out macroscopic traffic model scenarios. The research found that analyzing the flow profile throughout the day enabled data to be more accurately classified than using the total flow for the entire day. Caceres et al. [26] applied hierarchical cluster analysis to historical hourly traffic flow data. However, the clustering is performed to categorize roads by their "attractiveness factor" using a simple distance and population size gravity model. The average flow profiles of each cluster were then calculated and found to be representative of roads with specific characteristics. The shape of the diurnal flow profile could then be applied to roads without flow counters but that shared the characteristics consistent with a specific cluster, useful in transport modeling. Given the changes in peoples' travel behavior due to COVID-19, categorization of counters based on prepandemic attractiveness factors may not produce a reliable gravity model, such as the one in Caceres et al. [26], postpandemic. Moreover, if captured postpandemic, the flow profiles at each counter are likely to be different than the prepandemic flows assigned to clusters in that study. A greater understanding of how, due to the pandemic, travel demand has changed cycle flows over the day and depending on location is required.

Weijermars and van Berkum [25] found that preclassifying days into workdays and nonworkdays produced better clustering results, suggesting that the prevalence of commuting influences the shape of the diurnal flow profile. However, again because the COVID-19 pandemic has had such a profound effect on many aspects of life for the entire population it is not possible to precategorize flow profiles by day of the week in the same way.

More recently, other transport studies have used cluster analysis on data collected during the COVID-19 pandemic [27–29]; however, no previous research has explored the features of the daily hour by hour temporal changes in cycling flows (diurnal profiles) spatially across a region. The COVID-19 lockdown and restrictions have presented an opportunity to monitor and analyze the influence of travel demand by cycle when people were unable to work, children were not attending school, when restaurants and pubs reopened, etc. As such, this study makes a unique contribution to the ever-increasing number of studies providing evidence of the growing demand for cycling during the COVID-19 pandemic [14, 30, 31].

2. Research Methods

The data for the study were obtained from the inductive loop network in Tyne and Wear, UK, operated by the Traffic and Accident Data Unit (TADU) within Gateshead Council. TADU manages a dataset containing traffic accident, cycle, and traffic flow data for Tyne and Wear, a metropolitan county situated in the northeast region of England. The data provide a wealth of information to the local authorities to design, plan, and implement appropriate transport schemes across the county and enable academic institutions to carry out research. Tyne and Wear has a population of approximately 1.14 m people [32] across five local authorities: Gateshead, Newcastle upon Tyne, North Tyneside, South Tyneside, and Sunderland. Overall, it is a mix of urban, suburban, and rural environments, with Newcastle and Sunderland as the two cities within the county.

Despite having the highest proportion of households not owning a car in the UK outside of London (28%), 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 [33]. 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 [34]. As with the rest of the UK, the ownership and use of cars in the North East are growing, which will exacerbate the problems with congestion and hinder progress toward net zero [33].

As a response, the North East 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 motorized traffic cited as an important intervention [33]. While there have been some high-profile active travel infrastructure projects within the region, such as the reallocation of city center road space from motorized 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 motorized traffic. In the past, bike share schemes have been introduced in the region on two occasions, with Scratch Bikes operating in Newcastle and Sunderland (2011–2013), and Mobike in Newcastle and Gateshead (2017–2019). While there was no bike-share scheme operating during the 2020 lockdown, the Neuron e-scooter share scheme has been operating since the beginning of 2021 in Newcastle and Sunderland.

With reduced car use, the COVID-19 pandemic lockdowns of 2020 gave the region "cleaner and quieter towns, cities, and neighborhoods" [33]. Due to the reduced levels in motorized traffic, this window in time offers local authorities a unique insight into how cycling behaviors may change if future interventions were to replicate these conditions on a permanent basis, such as through the creation of segregated cycle routes and low traffic neighborhoods.

2.1. Data Collection and Preparation Stage. Cycling data were available from 25 counters, which were screened to ensure they were sufficiently operating during the lockdown period. The location of each cycle counter site is marked in Figure 1.

The locations are color-coded based on general location, and although not limited to the trip purposes described, anticipated trips are suggested in Table 1.

Cycle flow data captured from the database at the 25 sites were screened once more for any missing data during 2019. Data missing in 2019 were substituted with 2018, equivalent to 5.64% 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 [31], for the purpose of this initial study, this minor difference is considered acceptable, and substituting 2018 for 2019 data is deemed appropriate. The 2018/19 data will be referred to as the "Pre-COVID-19" year in this study. The cycle flow data can be treated as continuous because they come from 24-hr automatic cycle counters.

2.2. Key Dates of the COVID-19 Lockdown Restrictions in England. It is important to look at cycling flows in the context of the restrictions placed on society to curb the spread of COVID-19 at that given time. Below are the key dates during the study period.

(i) March 26, 2020: "Stay at home" lockdown measures legally enforced,
(ii) May 10, 2020: Return to the workplace if cannot work from home,
(iii) June 1, 2020: Phased reopening of schools in England,
(iv) June 15, 2020: Nonessential shops reopen in England,
(v) July 4, 2020: Reopening of pubs, restaurants, and hairdressers, and
(vi) August 14, 2020: Reopening of indoor theatres, bowling alleys, and soft play.

*Source–Institute for Government [35].

2.3. High-Level Analysis—t-test of Flows before and during COVID-19. Paired sample *t*-tests were carried out between the pre-COVID-19 year and 2020, to compare cycling volumes between the periods at each of the 25 sites. This determined whether there has been a statistically significant change in cycle flow volume during the lockdown and whether there is a pattern in terms of location. The null hypothesis is to assume no difference in the mean value at each site. Weekly flows between 1st March and 31st August during the pre-COVID-19 year and 2020 were loaded into SPSS software for the paired-sample *t*-test.

2.4. Main Analysis—Hierarchical Cluster Analysis of Daily Flow Profiles. The main analysis focuses on data clustering of daily flows to identify how the time of day and where people cycled changed during the 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-19 year and 2020, combined in one dataset with a total of 8,741 diurnal flow profiles amounting to 209,784 hourly flows.

While the *t*-test analysis is concerned with flow volumes, the primary objective of the clustering process is to group daily flows according to the shape of their daily flow profile. A factor that has to be considered when performing a single cluster analysis on the flows of 25 different sites is that the total flow volumes will differ across sites, as some will be inevitably used more than others. As a result, the formation of the clusters would be dominated by the total volume.

Therefore, a preprocessing exercise was performed to ensure the shape of the daily flow profiles drives the cluster memberships and not the total volume. The hourly flow volumes were converted into new values determined by their relation to the mean of the hourly flow for that given day at that specific site. This was calculated by dividing each hourly flow by the mean, after zero-centering by subtracting the mean.

Mathematically, the normalized count for each hour t over the day becomes the following:

$$N_t = \frac{q_t - \overline{q}_t}{\overline{q}_t}, \tag{1}$$

where

$$\begin{aligned} N_t &= \text{normalised cycle count for each consecutive hour } t\text{, separately for each of the 24 hours across a day,} \\ q_t &= \text{actual measured cycle count for each consecutive hour } t\text{, separately for each of the 24 hours across a day,} \\ \overline{q}_t &= \text{mean hourly count averaged over the 24 hours across a day} = \overline{q}_t = \frac{\sum_{t=1}^{24} q_t}{24}. \end{aligned} \tag{2}$$

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

This maintains the 24-hour time series diurnal structure of the data while neutralizing the effect of largely different flow volumes, therefore, allowing the shape of the flow profiles to be the determining factor in the clustering process.

As the cycle flow data are treated as a continuous variable, the hierarchical cluster analysis (HCA) approach was applied using SPSS software. The HCA is particularly suitable for analyzing traffic flow profiles [25, 26] However, unlike Weijermars and van Berkum, due to the unprecedented effect that the lockdown had on travel in 2020, the data were not preclassified. Instead, the proposed approach allows the patterns in the hourly cycle flows to drive the clustering seamlessly across COVID-19 lockdown days and historical flow profiles.

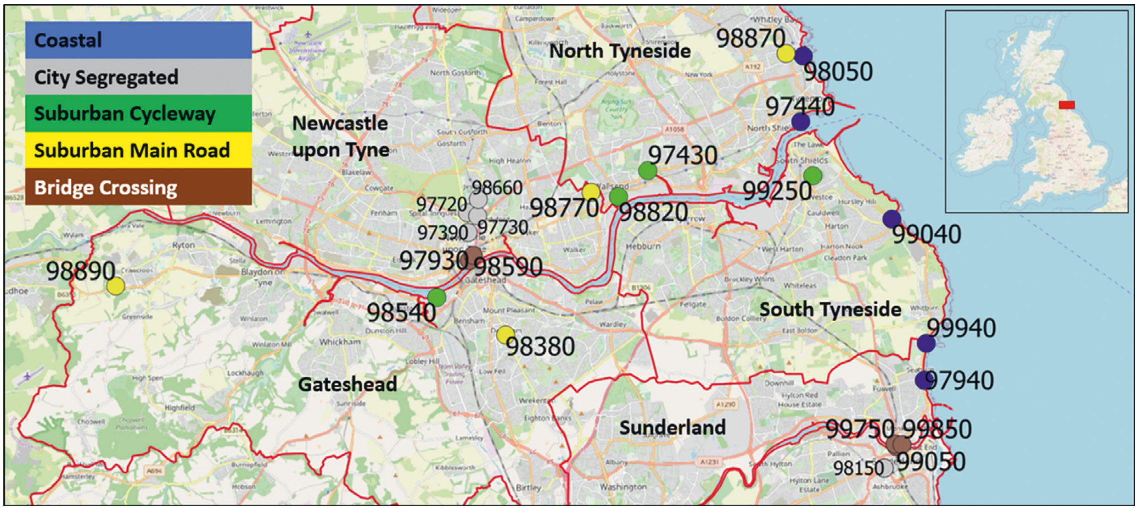
The HCA is a form of "bottom-up" agglomerative clustering technique where each of the 8,741 diurnal flows is treated as a separate cluster at the beginning of the agglomeration process, combining the most similar clusters one step at a time, creating new ones until the data are categorized into the desired number of clusters. The similarity between flow profiles was determined by the Euclidean distance across each normalized hourly flow. Ward's linkage was the method chosen to cluster the data, which minimizes the variance of the merged clusters and seeks to avoid clusters with a small membership.

Determining the number of clusters to categorize the data is a subjective process. Generally, a "gap" is identified where an increase in a number of clusters produces only a small reduction in the variation among clusters [36]. This can be identified through plotting the agglomeration coefficients at each stage of the clustering process to produce a scree plot for interpretation. Due to the subjective nature of this step, the three authors decided together on the number of clusters to categorize the data, the results of which are shown in the next section. Once each daily flow has been assigned a cluster membership, a more detailed investigation into characterizing the shift in cycling patterns as a result of the pandemic could begin.

2.5. Research Outcomes. The outcomes were compared and contrasted with previous studies to benchmark this research with the wider literature. The outputs from each step in the data analysis were collated together and through a discussion, and connections and consistencies in the outputs were identified. In this way, evidence that supports future policy and informs decision-making with regard to the implementation of future cycling schemes was articulated.

3. Results

In this section, the results are presented in three stages. First, the *t*-test was used to explore the changes in the weekly flow levels generally across Tyne and Wear. This is followed by the more technical HCA. Finally, by integrating the HCA outputs with the *t*-test results, any relationships between the change in flows and the prevalence of a particular shape of the diurnal cycling flow profile were determined. This is analyzed with reference to geospatial and temporal factors, including investigating the impacts of the different levels of government restrictions during the lockdown.



*Base map and data from OpenStreetMap and OpenStreetMap Foundation

Figure 1: Location of the 25 sites. *Base map and data from OpenStreetMap and OpenStreetMap Foundation.

Table 1: Cycling induction loop counter location types.

Colour		Counter location type	Description	Anticipated trips
Blue		Coastal	Coastal counters are segregated from motorized traffic and directly fronting the North Sea	Recreational
Gray		City	Segregated counters within or on the edge of the city center	Commute, studying, and shopping
Brown		Bridge crossing	Segregated counters on bridges or in their immediate vicinity, over the River Tyne or Wear	Commute, shopping, and recreational
Green		Suburban cycleway	A segregated cycle path in a suburban area.	Commute, school trips, recreational, and grocery shopping
Yellow		Suburban main road	Main road shared with motorized traffic in a suburban area	Commute and grocery shopping

3.1. The t-test—Change in Total Volume. Figure 2 shows the average change in weekly cycle flows from 1st March to 31st August from the pre-COVID-19 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, while 13% of detectors remained relatively unchanged. A t-test was carried out to establish statistical differences in the weekly flows between pre-COVID-19 and 2020. The ±95% about the difference in mean for each detector is plotted in Figure 3, expressed as a percentage. The counters exhibiting increases were mainly coastal sites, and those experiencing a decrease were in the city areas and those showing a moderate increase were the suburban cycleways and alongside suburban main roads.

3.2. Hierarchical Cluster Analysis Results

3.2.1. Determining the Number of Clusters. Using the scree plot technique described earlier in this study suggested that the optimal number of clusters for the data lies between 2 and 8. In order to identify the optimal number of clusters, the HCA was systematically performed from 2 up to 8 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. The results of the scree plot can be seen in Figure 4.

The daily flow profiles are categorized into a marginally decreasing number of clusters, the final six stages of which can be followed starting at the bottom of Figure 5 and

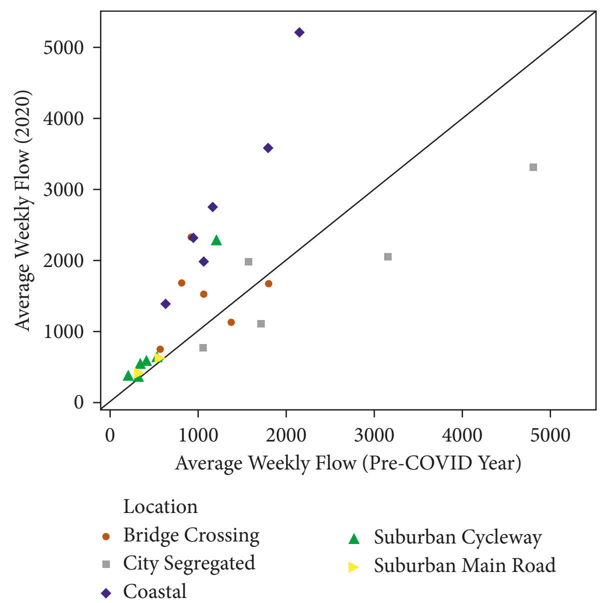


FIGURE 2: Change in average weekly flow pre/during COVID-19.

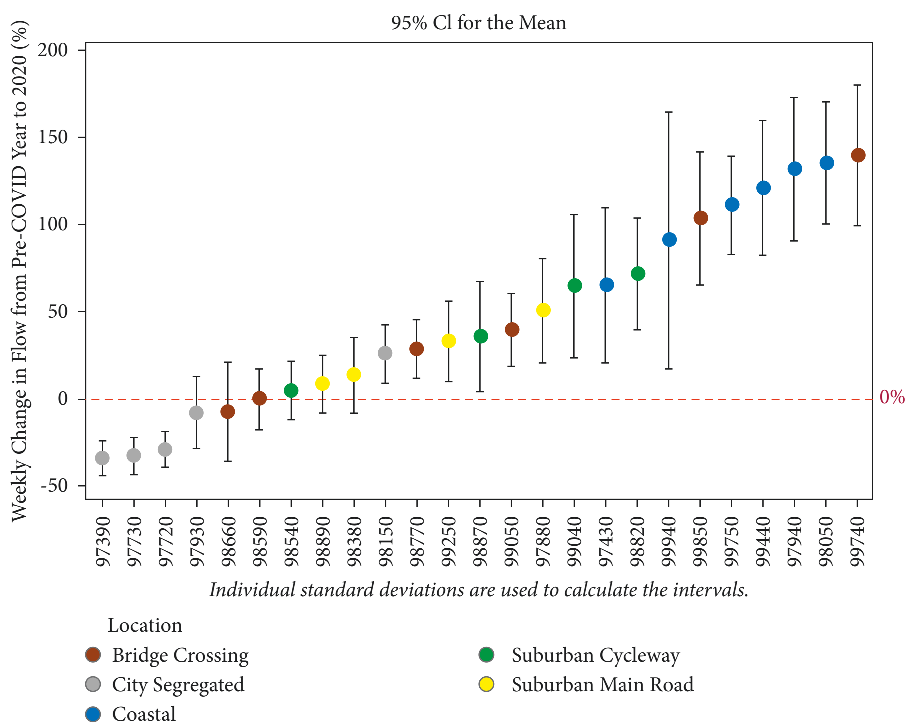


FIGURE 3: *t*-test change in average weekly flow pre/during COVID-19.

working upward. Clusters are highlighted in red that join together in the next agglomeration step. While 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 downward. 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 the authors 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.

3.2.2. Characterizing 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, the trip purpose

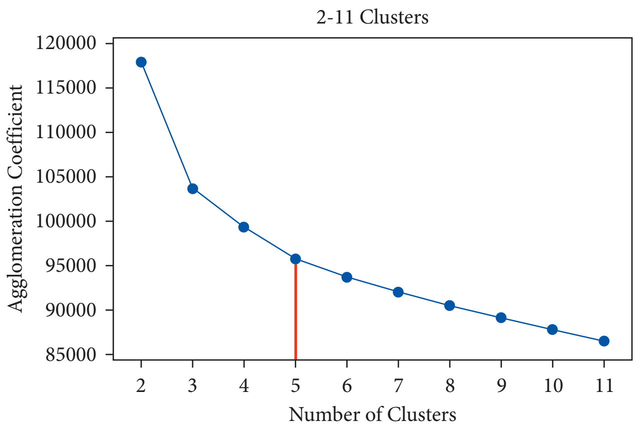


Figure 4: Plot of agglomeration coefficient against a number of clusters.

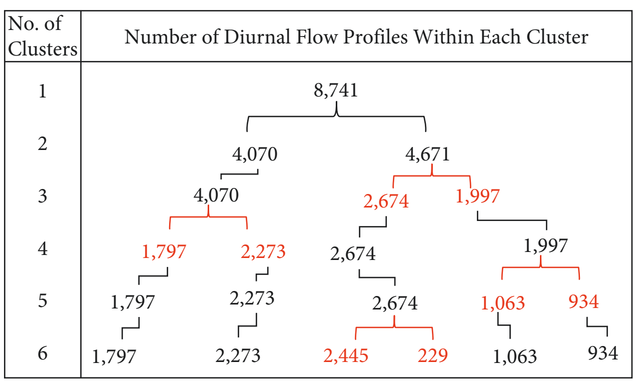


Figure 5: Cluster membership for 1–6 clusters.

will be influencing cluster membership, i.e., whether commuting or noncommuting. In this section, the characteristics of daily flows within each cluster are explored.

3.2.3. Diurnal Profiles. With reference to Figure 6, Cluster 1 exhibits a monotonic increase to a peak at 17:00 h and a rapid fall while Cluster 2 shows a gradual rise in the morning up to noon and then a flattening before gradually falling after 16:00 h. Cluster 3 is typical of a commute profile with a morning peak period from 06:00 h–09:00 h and evening peak 15:00 h–18:00 h. Cluster 4 exhibits a rise to a peak at 10:00 h–12:00 h and a gradual monotonic fall while Cluster 5 rapidly rises peaking at 10:00 h and falls monotonically reaching zero at midnight.

The clusters have been given titles according to these characteristics, and Clusters 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 2 provides an overview of the characteristics of the diurnal flows associated with each cluster, which will be discussed in the remainder of this section.

3.2.4. Cluster Membership across Pre-COVID-19 Year and 2020. The number of daily profiles categorized 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 been substantially fewer. But generally, the clusters are of similar magnitude, a trait of Ward's method.

Table 2 shows that two of the five flow profile clusters are less evenly distributed across the pre-COVID-19 year and 2020 than the other three profiles. About 39% of the mid-day steady cluster flows occurred in the pre-COVID-19 year with the other 61% in 2020. The traditional commute cluster saw the reverse of this trend, with 59% in the pre-COVID-19 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-19 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.

3.2.5. Days of the Week. Table 2 shows that each cluster comprises of different proportions of days of the week, so as to gain a richer understanding, the data were plotted in Figure 7 to show the number of days that fall into each cluster (a) during pre-COVID-19 year and (b) during 2020. While the "mid-day steady" and "late morning peak" profiles have slightly more weekend days clustered within them compared to weekdays, it is the cluster characterized by the mid-morning peak's profile that 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 a higher number of pre-COVID-19 compared to 2020 during COVID-19, as expected as people WFH. "Evening-only peak" shows a slight fall during COVID-19 compared to pre-COVID-19.

3.2.6. Location of Counter. The next step was to investigate how the composition of the cluster changes with the location of the cycle detector site as shown in Figure 8. The traditional commute and evening-only peak clusters contained diurnal flows from mostly city center or bridge locations, while mid-day steady, late morning peak, and mid-morning peak were predominantly coastal. Worthy of note is the substantial lack of city locations in the late morning peak and mid-morning peak. The descriptive statistics in Table 2 indicate that the characteristics of the city locations are different from those at the coast, which is consistent with the differences found in the shape of the diurnal hourly cycle flows.

The data were disaggregated according to the stage of lockdown, characterized 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 9.

The mid-day steady cluster approximately doubled in prevalence from 24% of total pre-COVID-19 flows to 49% during COVID-19 time. As people return to work, shops, schools, and hospitality opens, the proportion declines,

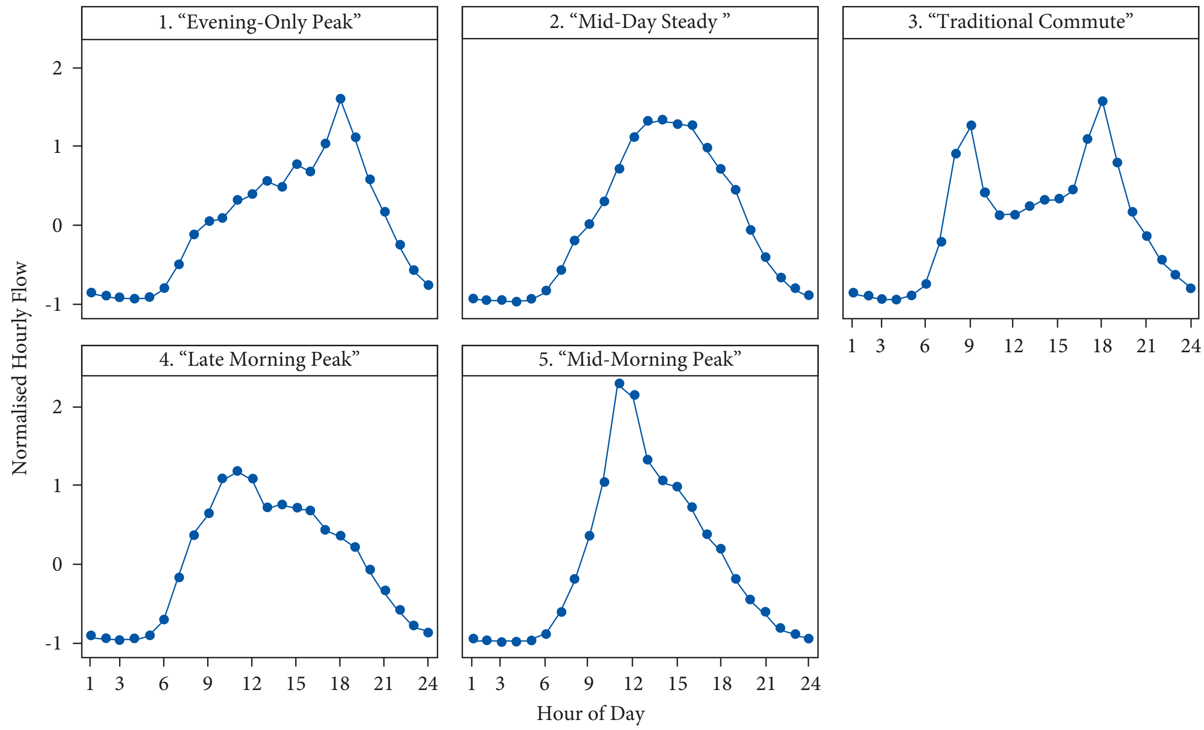


FIGURE 6: Average daily flow profile of each cluster.

TABLE 2: 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	Traditional 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-19 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-19 lockdown Pre-March 26, 2020	57%	45%	67%	60%	61%

Table 2: Continued.

Value	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Full lockdown March 26-May 10, 2020	9%	21%	8%	9%	16%
Return to work May 11-May 31, 2020	5%	8%	4%	5%	6%
Partial school reopening June 1-July 3, 2020	10%	10%	9%	8%	4%
Hospitality reopening July 4-Aug 31, 2020	19%	16%	13%	18%	12%
Total	100%	100%	100%	100%	100%

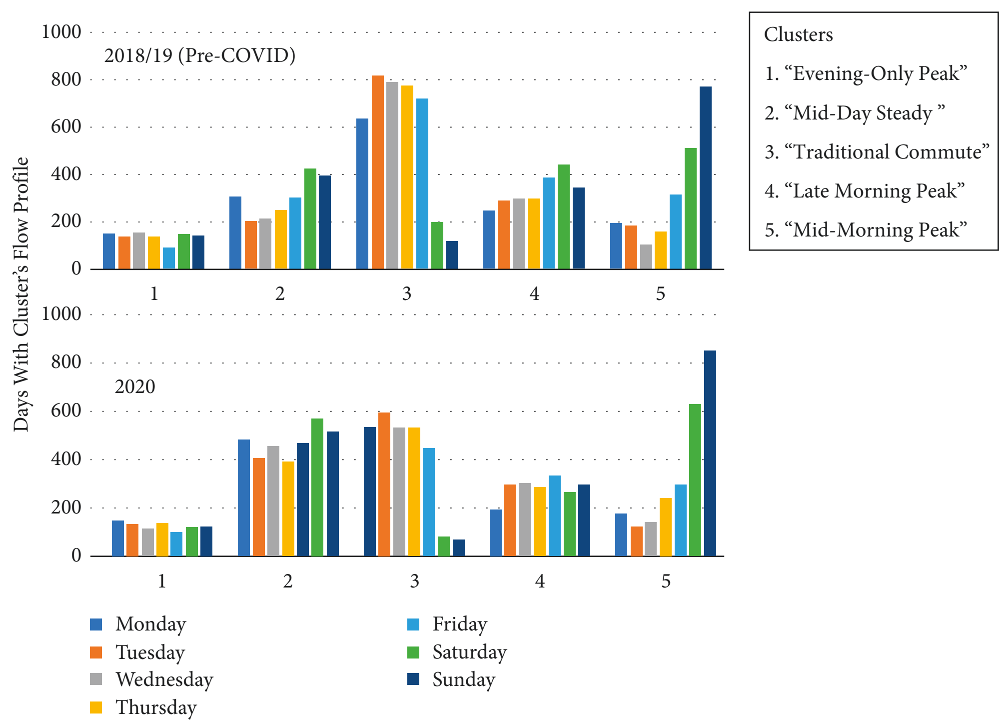


Figure 7: Cluster composition by day of week.

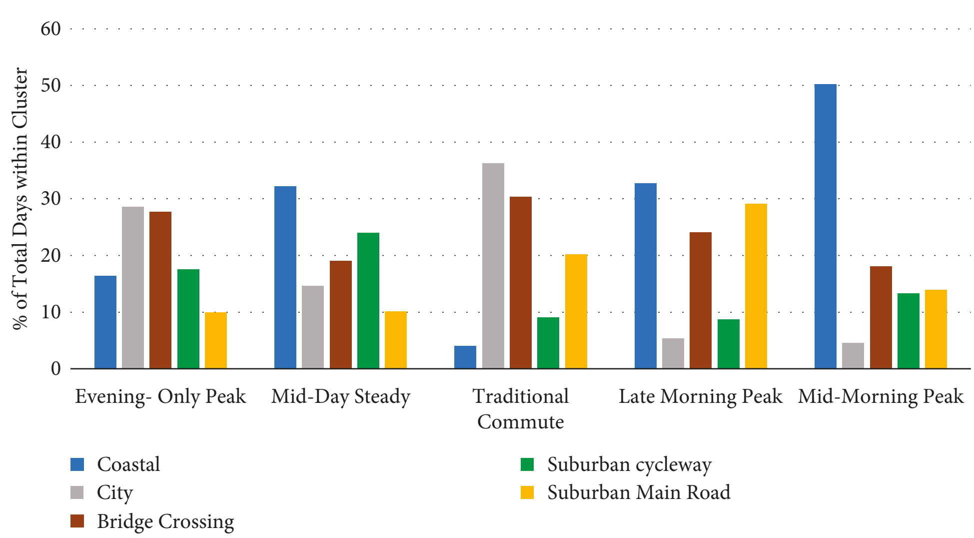


Figure 8: Cluster composition by counter location.

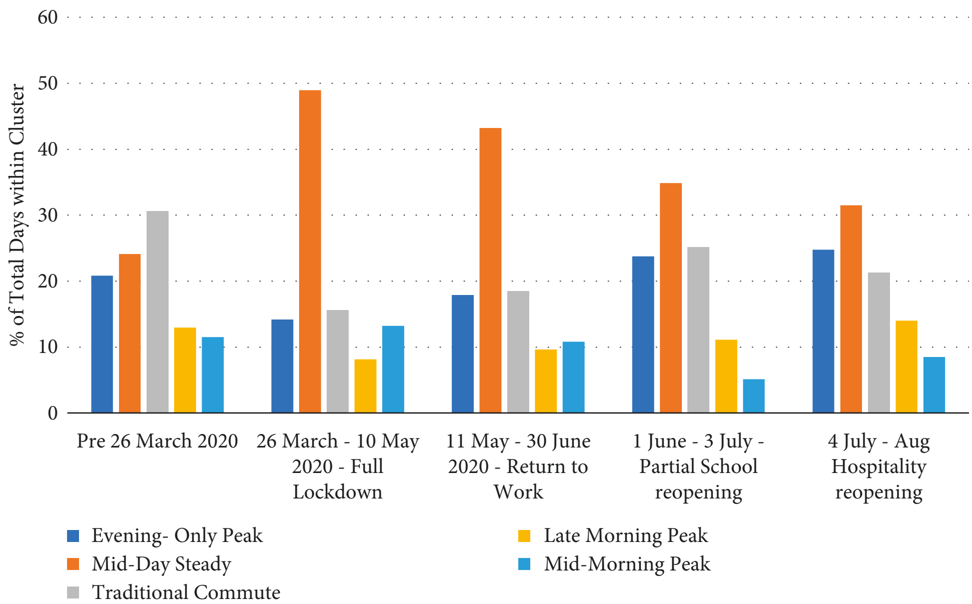


Figure 9: Changing flow profiles during each stage of lockdown.

although still higher than prelockdown levels at 31% of the total between the 4th of July and the end of August. This suggests that it is not solely due to the lack of alternative recreational activities that resorted to people choosing 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 the lockdown as a viable mode that they wish to cycle to the reopened cafes, theatres, and other reopened services.

The opposite occurs in the traditional commute cycle flow profile cluster. Pre-COVID-19, it is the dominant flow profile, representing 31% of the daily flows before dropping to 16% during the full lockdown. It gradually increases in prevalence as life returns to the "new-normal" but never reaches prelockdown levels as people continue to WFH, peaking at 25% of total flows before slightly dipping in August. In the UK, August typically experiences lower volumes of commuting traffic due to the school summer holidays [37], 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 the lockdown and gradually increase 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 prelockdown 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, and one suggestion is that both flow profiles are associated with new commuting practices postlockdown. 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 9 am; 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 9 am start but then disappearing before the traditional 5 pm finish.

Finally, the prevalence of mid-morning peak flows maintained relatively stable between 11 and 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 9 am start, but once it was necessary to be out of the house for the school run at that time it made more sense to link trips.

3.3. Integration of Outputs. The final step in the analysis links the prevalence of each clustered flow profile with a change in total flow volumes during COVID-19, disaggregated by location. Each graph within Figure 10 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.

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. The positive trend lines in the respective graphs within Figure 10 demonstrate this. It

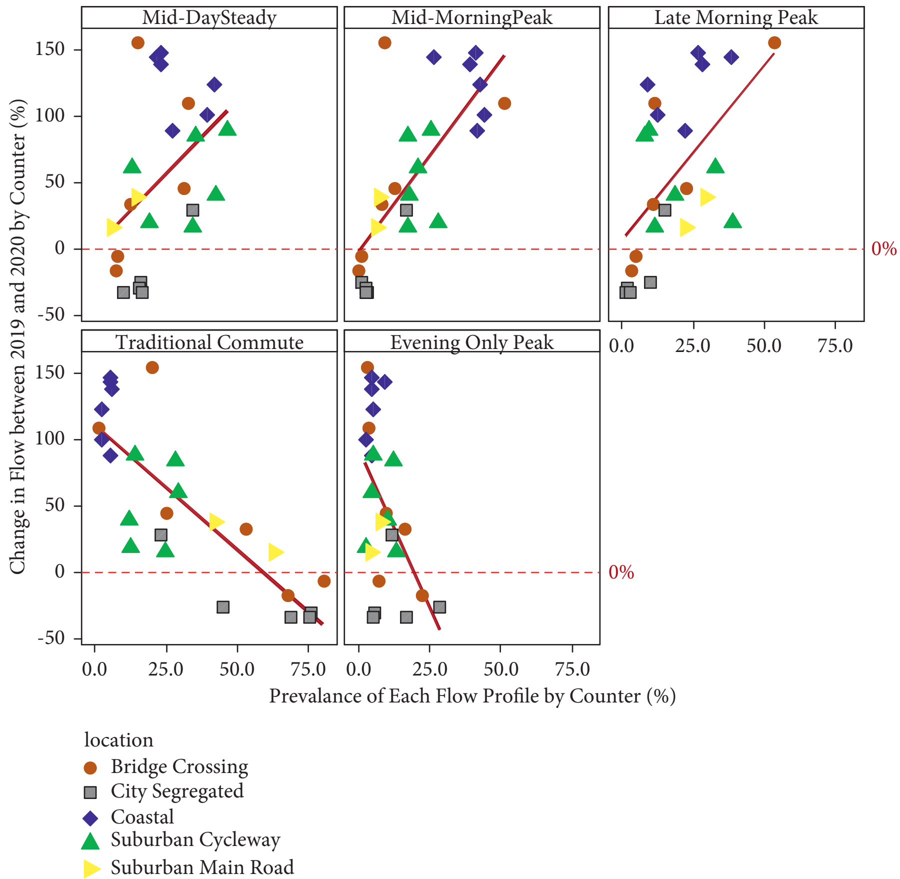


Figure 10: Cluster prevalence at each counter and the change in total flow.

can be seen that the counters at coastal sites tended to have the highest prevalence of these flow profiles and the highest increases in overall flows during COVID-19 lockdown. In stark contrast, counters with a higher prevalence of the traditional commute and evening-only flow profiles, such as the city center locations, were associated with a decrease in flow, as seen within the bottom two graphs within Figure 10.

Suburban cycleways and suburban main roads with middle levels of penetration in all clusters all exhibited moderate levels of increase in during COVID-19. This is consistent with Figures 2 and 3 that show that there was generally an overall increase in cycling volumes.

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 Figures 1 and 3). The Wear crossing is closer to the coast and a riverside cycleway, suggesting it could be recreational routes driving their demand. In contrast, the bridge crossings over the River Tyne (97930 and 98590 in Figures 1 and 3) 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 to commuters.

The graphs in Figure 10 suggest that the prevalence of each cluster is related to the change in flows during COVID-19 compared to pre-COVID-19; therefore, a linear relationship was fitted. Using Pearson's coefficient, it is clear at the 95% confidence level that linear relationships exist within all five clusters, as illustrated in Table 3. It further demonstrates that the mid-day steady (0.754) and the traditional commute are the two flow profiles that provide the largest contrast in the data, with the former possessing the strongest positive (0.754) and the latter the strongest negative (-0.820) correlation with the change in flow during lockdown restrictions.

Table 3: Correlation between cluster prevalence and change in flows from pre-COVID baseline (Mar–Aug) compared to 2020 (Mar–Aug).

Cluster	Pearson's correlation	P value
Mid-morning peak	0.754	$P \leq 0.001$
Late morning peak	0.578	0.002
Mid-day steady	0.439	0.028
Evening-only peak	−0.508	0.010
Traditional commute	−0.82	$P \leq 0.001$

4. Discussion

4.1. Suitability of Hierarchical Cluster Analysis of Cycle Flow Profiles. While previous use of HCA has focused on flow profiles of motorized vehicles, this research has demonstrated by studying the impact of COVID-19 on bicycle flows that HCA is a flexible tool that can be utilized in a wide range of flow types and locations, to quantify the impact of new situations of which we had no previous experience. By obtaining valuable results without preclassifying the data as per previous studies [25, 26], the flexibility of this methodology is demonstrated further. This paves the way for testing the methodology on subsequent datasets. Though this study looked at the impact of COVID-19, future uses could assess the impact on both cycle and motorized vehicle flows with the introduction of policy measures aimed at achieving a "Green Recovery" or net zero, such as low-traffic neighborhoods, 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 [5].

The HCA proved to be effective in predicting whether a flow profile was strongly associated with commuting or noncommuting 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 center 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 noncommuting in nature. Further research is required beyond this to determine HCA's suitability to infer more detail of a noncommuting trip by flow profile alone.

While basic descriptive statistics, such as the paired sample *t*-test of change in flow volume, give 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 characterize cycling flows during the transition into a postpandemic era. Moreover, the impact of any future lockdowns, which look increasingly likely in light of the Omicron variant outbreak in December 2021, can be analyzed in a consistent way.

4.2. 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 noncommuting trips across Tyne and Wear increased throughout the period of COVID-19 restrictions, especially those near coastal and suburban areas. This is consistent with the Glaswegian study into the early stages of lockdown conducted by Hong et al. [14]. In terms of policy implication, these trips significantly contribute to the target set out in the UK Cycling and Walking Investment Strategy to double cycling trips from 2013 levels by 2025 [4]. As the target does not discriminate according to journey purpose, these trips will remain important after the pandemic, especially if the shift in culture to WFH becomes permanent. Any trips, once carried out by car that is replaced by bicycle, will be a positive contribution to achieving the wider sustainability goals 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 noncommuting trips such as recreation or visiting shops. By disaggregating the data by notable periods of lockdown restriction and easing, it reveals the mid-morning peak, late morning peak, and evening-only clusters increased when hospitality reopened, which we can speculate is consistent with noncommuting activities such as morning coffee or lunch and socializing in the evening. Weekends in pre-COVID-19 days and days after the hospitality sector reopening in 2020 were dominant in the mid-morning peak, which suggests it may be associated with shopping and socializing during the day in cafes, bars, and restaurants.

Suburban cycleways consistently fall in the medium prevalence of all the clusters with a medium increase in flows during COVID-19 relative to pre-COVID-19. This suggests that suburban cycleways are used for a range of trip purposes and, therefore, less likely to see reductions in flows than their city center 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 motorized 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 noncommuting 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 realized once the perception of danger associated with cycling among 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 and segregated routes for cycling formed is in line with national government guidance.

Finally, the city center 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. [14]. As a further four months (May–August 2020) were included when compared to the Hong et al. study, this study is able to expand on the initial findings and observed cycle flows beyond the full lockdown period. This enabled the finding that commuting trips did show signs of returning to pre-COVID-19 levels as the lockdown was gradually eased in the subsequent months in the UK, that is, results consistent with commuter activity within the nationwide bike-sharing market reported in Nikitas et al. [18]. This section has touched upon the implications for policy in terms of noncommuting 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. While prior to the pandemic local authorities believed political barriers, namely, the fear that their core, car-driving voters will be disillusioned by procycling schemes [5], 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 realized, will be inclusive in that all types of cyclists will benefit to some extent.

4.3. Opportunities for Further Study. Relating these findings back to Nikitas et al. [18], many temporary schemes failed due to a lack of understanding of the needs of the users, possessing this additional information regarding flow profile enables transport planners to decide whether to prioritize direct, faster routes (i.e., for regular commuters), or safety and segregation for attracting less confident, noncommuters from a wider sociodemographic background [6–10]. Future research of a qualitative nature could be conducted considering the findings presented in this manuscript. Surveys and focus groups could identify 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 revealed in this study to experience the greatest increase in cyclist flows. Given this number of new cyclists, it would be useful to understand motivation and to cocreate interventions that would encourage them to continue to cycle postpandemic. Identifying future cycling infrastructure projects in this way maximizes the benefits of local authority investment at a time of budget constraints.

Furthermore, the HCA will be periodically performed with cycle flows to gain an understanding of how the flow profiles change in the postpandemic near future. That being said, like many countries in the world, the UK is not free of COVID-19, as evident from the reinstatement of WFH guidance in the UK as recent as of December 13, 2021, due to the impact of the Omicron variant. Monitoring of cycling volumes and transport patterns in relation to lockdowns and changes in restrictions will continue beyond 2022, providing an opportunity to apply the methodology presented in this manuscript, and continue to enrich the knowledge base.

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

While 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 morning and evening peaks; however, it is not possible to infer the trip purpose beyond commuting/noncommuting with flow profiles alone. While the changes to lockdown restrictions provided some insight into how the trip profiles changed as different sectors reopened, without specifically asking a cyclist 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 weekdays and nonweekdays, as would the qualitative research, described in the previous section.

5. Conclusions

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 decarbonizing 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 conclusions can be drawn from this research:

(i) HCA is a flexible tool that can be transferred to any location with appropriate flow data and utilized to quantify the impact on cycle flows of relatively unknown situations, the example presented in this research being the COVID-19 pandemic lockdown;

(ii) The overall volume of cycling substantially increased as a result of UK government-implemented lockdown restrictions within the case study area of Tyne and Wear, as experienced in previous studies;

(iii) HCA of daily flow profiles and subsequent disaggregation of the data provides additional insight to decision-makers 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;

(iv) Noncommuting flow profiles saw the largest increase during the lockdown, in locations closer to suburban or recreational opportunities; therefore, planners should consider catering to 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;

(v) As lockdown restrictions eased, flow profiles began to revert back to the prepandemic 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;

(vi) This study demonstrates that substantial increases in cycling flows can be achieved given the right conditions. While the increased popularity of cycling during the pandemic had short-term benefits, the consequential increased cycling advocacy and political will potentially contribute to longer-term cycling policy aims, paving the way for more ambitious investment in cycling infrastructure that will benefit all cyclists and trip purposes.

Data Availability

The data are from the public domain. This is the link: https://www.gateshead.gov.uk/article/4464/Traffic-and-Accident-Data-Unit.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

The authors confirm their contribution to the paper as follows: Matthew Burke: 40%, Dilum Dissanayake: 30%, and Margaret Bell: 30% contributed to study conception and design. Matthew Burke: 80%, Dilum Dissanayake: 10%, and Margaret Bell: 10% contributed to data collection. Matthew Burke: 60%, Dilum Dissanayake: 20%, and Margaret Bell: 20% contributed to analysis and interpretation of results. Matthew Burke: 70%, Dilum Dissanayake: 15%, and Margaret Bell: 15% drafted manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

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References

[1] Carbon Brief, "Coronavirus: tracking how the world's 'green recovery' plans aim to cut emissions," 2021, https://www.carbonbrief.org/coronavirus-tracking-how-the-worlds-green-recovery-plans-aim-to-cut-emissions.

[2] Department for Business, Energy & Industrial Strategy, "UK enshrines new target in law to slash emissions by 78% by 2035," 2021, https://www.gov.uk/government/news/uk-enshrines-new-target-in-law-to-slash-emissions-by-78-by-2035.

[3] Department for Transport, "Cycling and walking investment Strategy," 2022, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/918442/cycling-walking-investment-strategy.pdf.

[4] U. K. Cycling, "Government in serious danger of missing cycling and walking targets, say leading charities," 2021, https://www.cyclinguk.org/press-release/government-serious-danger-missing-cycling-and-walking-targets-say-leading-charities.

[5] R. Aldred, T. Watson, R. Lovelace, and J. Woodcock, "Barriers to investing in cycling: stakeholder views from England," *Transportation Research Part A: Policy and Practice*, vol. 128, pp. 149–159, 2019.

[6] D. Dissanayake, "Watching the clock on the way to work? Analysing trends in commuting activities, modes and gender differences in commute times, using hazard-based duration modelling methods," *Journal of Transport Geography*, vol. 65, pp. 188–199, 2017.

[7] R. Steinbach, J. Green, J. Datta, and P. Edwards, "Cycling and the city: a case study of how gendered, ethnic and class identities can shape healthy transport choices," *Social Science & Medicine*, vol. 72, no. 7, pp. 1123–1130, 2011.

[8] T. Rossetti, V. Saud, and R. Hurtubia, "I want to ride it where I like: measuring design preferences in cycling infrastructure," *Transportation*, vol. 46, no. 3, pp. 697–718, 2017.

[9] K. Kircher, J. Ihlström, S. Nygårdhs, and C. Ahlstrom, "Cyclist efficiency and its dependence on infrastructure and usual speed," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 54, pp. 148–158, 2018.

[10] J. Broach, J. Dill, and J. Gliebe, "Where do cyclists ride? A route choice model developed with revealed preference GPS data," *Transportation Research Part A: Policy and Practice*, vol. 46, no. 10, pp. 1730–1740, 2012.

[11] Department for Transport, "Road Traffic Estimates: Great Britain 2020," 2021, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1028165/road-traffic-estimates-in-great-britain-2020.pdf.

[12] Department for Transport, "£2 billion package to create new era for cycling and walking," 2020, https://www.gov.uk/government/news/2-billion-package-to-create-new-era-for-cycling-and-walking.

[13] Bicycle Association, "The Impact of COVID-19 on the UK Cycling Market in 2020," 2020, https://www.bicycleassociation.org.uk/mds-2020-covid-impact-report/.

[14] J. Hong, D. McArthur, and V. Raturi, "Did safe cycling infrastructure still matter during a COVID-19 lockdown?" *Sustainability*, vol. 12, no. 20, pp. 8672–2020, 2020.

[15] G. Lozzi, M. Rodrigues, E. Marcucci, T. Teoh, V. Gatta, and V. Pacelli, *Research for TRAN Committee – COVID-19 and Urban Mobility: Impacts and Perspectives*, European Parliament, Policy Department for Structural and Cohesion Policies, Brussels, Belgium, 2020.

[16] L. Barbarossa, "The post pandemic city: challenges and opportunities for a non-motorized urban environment. An overview of Italian cases," *Sustainability*, vol. 12, no. 17, p. 7172, 2020.

[17] T. Campisi, S. Basbas, A. Skoufas, N. Akgün, D. Ticali, and G. Tesoriere, "The impact of COVID-19 pandemic on the resilience of sustainable mobility in sicily," *Sustainability*, vol. 12, no. 21, p. 8829, 2020.

[18] A. Nikitas, S. Tsigdinos, C. Karolemeas, E. Kourmpa, and E. Bakogiannis, "Cycling in the era of COVID-19: lessons learnt and best practice policy recommendations for a more bike-centric future," *Sustainability*, vol. 13, no. 9, p. 4620, 2021.

[19] R. J. Dunning and A. Nurse, "The Surprising Availability of Cycling and Walking Infrastructure through COVID-19," *Town Planning Review*, vol. 92, no. 2, 2020.

[20] J. H. M. Brooks, R. Tingay, and J. Varney, "Social distancing and COVID-19: an unprecedented active transport public health opportunity," *British Journal of Sports Medicine*, vol. 55, no. 8, pp. 411-412, 2020.

[21] A. A. Laverty, C. Millett, A. Majeed, and E. P. Vamos, "COVID-19 presents opportunities and threats to transport and health," *Journal of the Royal Society of Medicine*, vol. 113, no. 7, pp. 251–254, 2020.

[22] N. McIntyre, "Traffic Wars: who will win battle for city streets," 2021, https://www.theguardian.com/news/2021/mar/25/traffic-wars-who-will-win-the-battle-for-city-streets.

[23] D. Holland, ""Malicious" hijack of Newcastle bridge closure experiment exposed as 7,000 fake comments deleted. Chronicle," 2021, https://www.chroniclelive.co.uk/news/north-east-news/malicious-hijack-newcastle-bridge-closure-19868498.

[24] F. Crawford, D. P. Watling, and R. D. Connors, "A statistical method for estimating predictable differences between daily traffic flow profiles," *Transportation Research Part B: Methodological*, vol. 95, pp. 196–213, 2017.

[25] W. Weijermars and E. van Berkum, "Analyzing highway flow patterns using cluster analysis," in *Proceedings of the 2005 IEEE Intelligent Transportation Systems*, pp. 308–313, IEEE, Vienna, Austria, September 2005.

[26] N. Caceres, L. M. Romero, and F. G. Benitez, "Estimating traffic flow profiles according to a relative attractiveness factor," *Procedia - Social and Behavioral Sciences*, vol. 54, pp. 1115–1124, 2012.

[27] H. Gibbs, Y. Liu, C. A. B. Pearson et al., "Changing travel patterns in China during the early stages of the COVID-19 pandemic," *Nature Communications*, vol. 11, no. 1, p. 5012, 2020.

[28] M. Hosoe, M. Kuwano, and T. Moriyama, "A method for extracting travel patterns using data polishing," *Journal of Big Data*, vol. 8, no. 1, p. 13, 2021.

[29] F. Liu, W. Bi, W. Hao, F. Gao, and J. Tang, "An improved fuzzy trajectory clustering method for exploring urban travel patterns," *Journal of Advanced Transportation*, vol. 2021, Article ID 6651718, 13 pages, 2021.

[30] R. Buehler and J. Pucher, "COVID-19 impacts on cycling, 2019-2020," *Transport Reviews*, vol. 41, no. 4, pp. 393–400, 2021.

[31] S. Nordengen, L. B. Andersen, A. Riiser, and A. K. Solbraa, "National trends in cycling in light of the Norwegian bike traffic index," *International Journal of Environmental Research and Public Health*, vol. 18, no. 12, pp. 6198–2021, 2021.

[32] Nomis Labour Market Profile, "Tyne and Wear," 2021, https://www.nomisweb.co.uk/reports/lmp/la/1967128612/report.aspx?town=tyne.

[33] North East Joint Transport Committee, "North East Transport Plan 2021-2035," 2021, https://www.transportnortheast.gov.uk/wp-content/uploads/2021/10/AST004-Transport-Plan-A4-North-East-Transport-Plan.pdf.

[34] Department for Transport, "Annual traffic by vehicle type in North East. Road traffic statistics," 2021, https://roadtraffic.dft.gov.uk/regions/11.

[35] Institute for Government, "Timeline of UK coronavirus lockdowns," 2021, https://www.instituteforgovernment.org.uk/charts/uk-government-coronavirus-lockdowns.

[36] Ibm, "SPSS statistics 28.0.0," 2022, https://www.ibm.com/docs/en/spss-statistics/28.0.0?topic=automobiles-dendrogram.

[37] Department for Transport, "Road traffic estimates: great britain 2020," 2020, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/916749/road-traffic-estimates-in-great-britain-2019.pdf.