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Understanding the impacts of public transit disruptions on bikeshare schemes and cycling behaviours using spatiotemporal and graph-based analysis: A case study of four London Tube strikes

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ABSTRACT

Understanding the interactions between different travel modes is crucial for improving urban transport resilience, especially during times of disruption and transit failure. As a flexible and sustainable travel mode, bikeshare schemes are able to solve "first/last" mile problems in urban transit as well as provide an alternative to motorised traffic. This paper uses OD (origin and destination) trip data from the London Cycle Hire Scheme and temporal docking station bike availability data to explore the impact of four separate London Underground (Tube) strikes on bikeshare usage and behaviours. The results suggest that bikeshare usage generally rises in response to Tube disruptions, but the extent and nature of this rise in use varies according to the type of disruption. A novel measure of station pressure suggests that the scheme very quickly reaches saturated capacity and is unusable in certain parts of London during disruptions. A graph-based analysis reveals several changes in OD flow structures. This implies a modal shift from Tube to bikeshare and a change of route behaviours among bikeshare users. Weekday Tube strikes bring new behaviours and new OD pairs to the bike flow structures, whilst for weekend strikes existing patterns are consolidated. The corollary is that more heterogenous OD trip patterns are introduced by higher volumes of commuting trips and intense competition of cycles/docks. Cyclists are forced into using alternative (second or third preference) docking stations with new behaviours, and possibly users, as journeys that would otherwise be made via the Tube are made via bikeshare. This work comprehensively presents and compares the impacts of Tube strikes under varied circumstances and offers a detailed understanding of the changed cycling behaviours that could be used in transport planning and management.

1. Introduction

Public transit disruptions have become more frequent in recent years due to the increasing maintenance needs of ageing infrastructure, natural disasters as well as social and political events such as city-wide festivals and strikes (Zhu et al., 2017; Gonçalves and Ribeiro, 2020; Rahimi et al., 2020). Such events and disruptions can significantly affect the resilience of transportation systems. Disruptions have many different consequences across the transport network, and characterising them, as well as how travellers may respond to transit failures, can inform urban transport planning and decision-making. Among different travel modes in big cities, bikeshare schemes are low-cost, highly flexible and convenient (Shaheen et al., 2013). In urban contexts, they fill an important gap between pedestrian and vehicular transport (Curran, 2008), and can provide a genuine alternative travel mode when other parts of the transportation system experience disruptions. Previous research (Green et al., 2012; Zhu et al., 2017; Younes et al., 2019) has shown that disruptions to metro and bus systems may result in a shift to bikeshare schemes, especially for low-income groups, as bikeshare is a low-cost alternative to, for example, private taxi and minicab services.

Understanding the changes in cycling behaviour during transit disruptions is crucial for minimising the impacts in the short-term, but also benefits sustainable transport planning in the long-term (Dill and Carr, 2003; Zhu and Levinson, 2010). Mass transit disruptions can prompt

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new behaviours and introduce new people to cycling. Research has shown that many new cyclists used bikeshare in London during previous transit strikes (Green et al., 2012), and may have continued to use bikeshare schemes subsequently (Zhu and Levinson, 2010). A more contemporary context is the reduced public transport capacity as a result of public health outbreaks, which require social distancing. This is likely to lead to an increase in cycling activities. Quinn (2020) predicts a multi-fold increase of cycling in London post-lockdown, and several plans have been made to overhaul the capital's streets and public space. These include: (1) the rapid construction of a strategic cycling network to help reduce crowding on bus and metro services; and (2) the transformation of local town centres to allow people to walk and cycle where possible (Quinn, 2020). The impacts of reduced public transport on shifts to cycling may be determined from the analysis of historical bikeshare data, and the results can be used to inform related sustainable urban and transport planning.

During disruptions, a range of different travel behaviours emerge according to the spatiotemporal characteristics of the incidents. To understand the changes in travel behaviours, observational data need to be analysed within their spatial and temporal context. Such spatiotemporal analyses have been published (Vertesi, 2008; Zhu et al., 2017; Saberi et al., 2018), but not in a comprehensive and large-scale way, partly due to data availability. Large transit disruptions (e.g. Tube strikes) are relatively rare events, and difficult to compare whilst controlling across changing explanatory variables. Previous work has focused on changes in demand, i.e. related to user behaviour (Vertesi, 2008; Zhu et al., 2017; Saberi et al., 2018) and has not considered the resource supply such as the provision of cycles and cycle docks. Information on dock availability could provide supporting context to explain user behaviours and may also support bike scheme operators in their fleet management strategies, which include manually redistributing bikes.

Until recently, reliable "impact" and "behaviour change" analysis has been problematic due to a relative lack of historical time series data. However, the London Cycle Hire Scheme (LCHS) has been in operation since 2010, and each timestamped user trip has been continuously recorded over this period. This greatly benefits long-term service analysis (Lovelace et al., 2020) and comparative studies, for example, characterising how usage and behaviours change in response to different events and interventions (Beecham, 2015).

The work presented in this paper tries to address the above problems by examining four London Tube strike events and their impacts on LCHS using freely available bike OD (origin-destination) usage data and station availability data. These strikes have varied temporal and spatial characteristics, which results in distinct patterns of change in LCHS. Temporal, spatial and structural patterns are examined to consider the impacts of Tube (i.e. metro, Underground) strikes on bikeshare schemes. The results have the potential to support LCHS service provision, to guide strategies for filling public transport gaps and to strengthen transit resilience.

The structure of this paper is as follows: Section 2 reviews recent literature on bikeshare studies related to disruptions and user behaviour, and Section 3 introduces the methods as well as case study. The results are presented in Section 4, providing insight on user behaviour changes and scheme dynamics in bikeshare due to transit disruptions. Section 5 summarises and compares the findings to those of other research, before conclusions are drawn (Section 6).

2. Background

Transit disruptions can adversely affect transport network reliability and bring substantial economic, social and safety impacts to cities and travellers (Wilson, 2007; Bauernschuster et al., 2017; Pregnolato et al., 2017; Yu et al., 2020). To minimise the impacts, people may change their travel behaviours according to the characteristics of the disruption (Cairns et al., 2002a, 2002b). For example, a short-term disruption (e.g., transport strike or a bridge closure) may lead to temporary changes in travel mode, choosing alternative destinations, reductions in journey frequency, etc. The behaviours in response to disruptions may also become permanent as new travel habits emerge (Zhu and Levinson, 2010).

A number of studies have analysed individual perceptions of and preferred reactions to transit disruption using questionnaires and survey data (Tsuchiya et al., 2008; Fukasawa et al., 2012; Teng and Liu, 2015). These suggest that patterns of temporary modal shifts during transit disruptions are related to income (Zhu et al., 2017). Different sharing-economy travel options offer new ways to minimise the impact of transit service failure, with wealthier people more likely to switch to taxis or car ridesharing (e.g. Uber, Lyft), and people with lower incomes choosing lower-cost mobility services such as bikeshare (Zhu et al., 2017). Studies evaluating the impact of transit disruption on bikeshare usage are critical for mitigating the impacts for disadvantaged groups.

Many large cities such as London have introduced bikeshare schemes composed of a network of docking stations and bikes into their urban centres. They are used heavily by tourists and commuters, especially for short journeys that would otherwise be made by bus and metro (Shaheen et al., 2013). Bikeshare works well when linked to public transport, solving the so-called `first/last" mile problem in urban transit – for example, by supporting short connecting trips from a major transport hub to a workplace or home (Yang et al., 2019). The majority of bikeshare studies can be grouped into two classes (Beecham, 2015): exploratory studies analysing variations in scheme usage related to the built and social-spatial environment (Faghih-Imani et al., 2014; El-Assi et al., 2017); and more narrowly-focused studies developing algorithms for supporting fleet management and rebalancing (De Chardon et al., 2016). Nello-Deakin (2020) suggest that over the last twenty years there has been an abundance of empirical studies with similar conclusions drawn, namely that urban environments with dedicated cycling infrastructure, traffic calming measures and moderate to high urban densities are associated with higher cycling rates (Nello-Deakin, 2020) and bikeshare usage (El-Assi et al., 2017). Numerous algorithmic approaches have been proposed in the literature to solve the traffic prediction and rebalancing problems (De Chardon et al., 2016; Pan et al., 2019). In contrast, there are comparatively few studies examining the interdependence between bikeshare and other transit modes, especially during disruption events or infrastructure changes.

Transit disruptions clearly have the most direct impact on public transport provision and influence bikeshare use substantially (Chen et al., 2016). The work of Chen et al. (2016) combined bikeshare usage data in New York with event data from multiple sources (Twitter, traffic data live feeds) to rank the impact of various social and transportation events on bikeshare. They suggest that metro delays have a much larger impact on bikeshare use than other disruption events such as surface road congestion and restrictions. Metro strikes (or closure for maintenance) are not included in Chen et al. (2016) 's events data set, and it is reasonable to speculate that they may have a higher or at least similar level of influence on bike ridership. This is due to the fact that strikes will make the metro service unavailable for a longer period, thus providing a more radical disruption than a delay to the schedule. Although highlighting the importance of understanding interdependence between metro and bike, the work of Chen et al. (2016) does not extensively explore changes in spatiotemporal patterns of bikeshare scheme use.

Further exploration into bikeshare ridership change may benefit scheme management activities, improve equity in mobility service provision, as well as long-term traffic planning. "Novice" cyclists who are not familiar with biking also make comparatively more trips on metro strike days (Green et al., 2012). These examples provide evidence that transit disruptions can introduce bikeshare to new users, potentially promoting and increasing cycling rates in the long-term.

Reviewing the literature has demonstrated that transport users may look to bikeshare as an alternative to public transport during metro service failures. However, there is comparatively little research quantitatively examining changes in usage patterns in bikeshare schemes while metro services are in disruption. Among the limited number of studies, Younes et al. (2019) analysed the impact of metro station closure for maintenance (a.k.a "Surge") on bikeshare demand. They found that the "Surge" can lead to between 24% and 45% more trips in bikeshare stations within 0.5 mile to metro. However, Surges are very different to network- or line-level metro disruptions, because they operate over small spatial scales. Typically, only several (e.g. up to three) metro stations are closed for maintenance (Younes et al., 2019); therefore, travellers often find alternative routes within the metro station network. Network-level disruption is examined in the work of Saberi et al. (2018), which characterised the impact of a weekday Tube strike on all lines and stations in London, along with its effects on LCHS. The work suggests that the ridership increase shows a significant distance decay pattern: the closer a docking station is to metro lines, the higher ridership increase it will experience. However, the findings may only be applicable for weekdays, when a lot of journeys are made for commuting purposes to complete the "last-mile" between the Tube or rail station and workplace. It is unclear whether this pattern still holds if the disruptions fall on holidays or weekends.

Over thirty strikes have occurred on London's Tube network since 2010 (Transport for London, 2017). These are caused by a mixture of factors, including disputes related to pay, safety, pensions and job security issues. The strikes may happen at the whole network-level, where at least the majority of the Tube service is unavailable, or at individual line-level, where only certain lines are disrupted. Impacts of these incidents on LCHS use will clearly be different depending on where and when disruptions occur as well as the duration of the disruption. According to Transport for London (2017), line-level strikes are more common in the London Tube than network-level strikes. Despite this higher frequency, the impact of line-level incidents on bikeshare has rarely been examined in previous studies. An exception is Yang et al. (2019), which analyses how the introduction of a new metro line service stimulates bike sharing ridership. Data from new forms of bikeshare (dockless) are examined, which provide higher spatiotemporal granularity for understanding cycling activities and urban flows in the last mile. Yang et al. (2019) analyse the more flexible travel OD pairs in the dockless scheme, and the study indicates how a new metro line can rapidly boost local bike travel demand and result in emerging parking clusters within 250 m around new metro stations. The work also highlights the structural changes caused by new OD pairs (when cast into a graph), capturing system-level adaptations and responses to changes in demand. Although this work focused on the impact of new metro lines, the graph structure and metrics it used suggest research opportunities for quantifying large-scale behavioural responses to line-level disruption.

Whilst the existing literature (Saberi et al., 2018; Yang et al., 2019; Younes et al., 2019) has evaluated the impact of events using travel records on patterns of use (demand), the dynamics of bikeshare service supply have yet to be examined. Metro disruptions pose significant management problems for bikeshare scheme operators (Younes et al., 2019), even if daily total trip frequencies do not substantially increase. Docking stations should always have cycles and empty docks available, but metro incidents may break this balance (Saberi et al., 2018). The dynamics in docking station capacity during disruptions have yet to be comprehensively analysed. The work presented in this paper starts to address the above gaps, by examining spatiotemporal and structural changes in bikeshare schemes in relation to metro (Tube) strikes.

3. Method

3.1. Case study: London cycle hire scheme (LCHS) and tube strikes

The LCHS was launched by London's public transport authority, Transport for London (TfL), in June 2010, initially with 315 docking stations and 5000 bikes. The scheme expanded its service significantly with more bikes and larger coverage areas in March 2012 and December 2013. By 2014, it had become the world's second-largest bikeshare scheme (Fishman, 2016), covering mostly central London. Due to the high prevalence of commuting activities, many LCHS trips are made to link travellers' home, workplace and transit hubs. This presents a solution to the "first/last mile" problem by combining with train and Tube trips, but this combination can be interrupted during transit disruptions.

Whilst there have been more than 30 London Tube strikes over the last decade (Transport for London, 2017), several factors must be considered when studying the effect of such events on LCHS use. Both weather conditions and particular calendar events may also significantly change bikeshare use, thus introducing uncertainties when comparing bike ridership patterns between strike and non-strike days. To control for these types of events, this work only focuses on rain-free day Tube strikes, and not on national holidays such as Christmas or bank holidays. A total of four Tube strikes have been selected (Table 1), with two at network-level and two at line-level. Among these incidents, Strike 2 was at a weekend, while the others occurred on weekdays. A map of the London Tube and bike docking stations is shown in Fig. 1. The Piccadilly line is the fourth busiest line in the London Tube network, and serves many of London's key tourist attractions, including Harrods, Hyde Park and Buckingham Palace. It also connects with the major London King's Cross railway station. The Central line is the second busiest line, running through Oxford Street and the financial centre of the City of London. The Waterloo & City line is a shuttle line that runs between Waterloo and Bank with no intermediate stops. Its primary traffic consists of commuters from south-west London, Surrey and Hampshire arriving at Waterloo station and connecting to the City, London's financial district.

3.2. Data

3.2.1. London cycle hire scheme (LCHS) trip data

The LCHS data detailing trip origin-destination pairs (OD) is published by Transport for London (TfL), covering the period from 2010 to present (2020), and can be retrieved using the R package ***bikeshare*** (Padgham and Ellison, 2017). Pre-processing work was carried out to remove redundant/duplicated and incomplete/faulty records from raw data. Each record in the cleaned dataset describes a single bike trip in the LCHS and contains complete information describing a trip's start and end docking station, with associated timestamps. Therefore the trip OD flows can be examined in some spatial and temporal detail. Because the data covers over a decade, it can support longer-term analysis of the evolution of the scheme (Lovelace et al., 2020), or to understand and compare the behaviours and dynamics in LCHS during different events and periods, such as holidays, lock-down, and transit disruptions. In this research, bike travel records on four different strike days and their respective corresponding two non-strike days are examined and compared. To quantify the changes caused by Tube strikes, bike data on strike days (listed in Table 1), their two nearest rain-free days of the same day of the week are used for comparison (Saberi et al., 2018). For example, if a strike happened on Friday, then data of the previous and subsequent Fridays (both rain-free) are used. Docking station location

Table 1
London Tube strikes.

Name	Category	Date	Tube Line	Day
Strike 1	Network-level	2015/07/09	All Tube lines	Weekday
Strike 2	Network-level	2015/03/07	All Tube lines	Weekend
Strike 3	Line-level	2018/09/27	Piccadilly line	Weekday
Strike 4	Line-level	2018/10/05	Central line, Waterloo & City line	Weekday

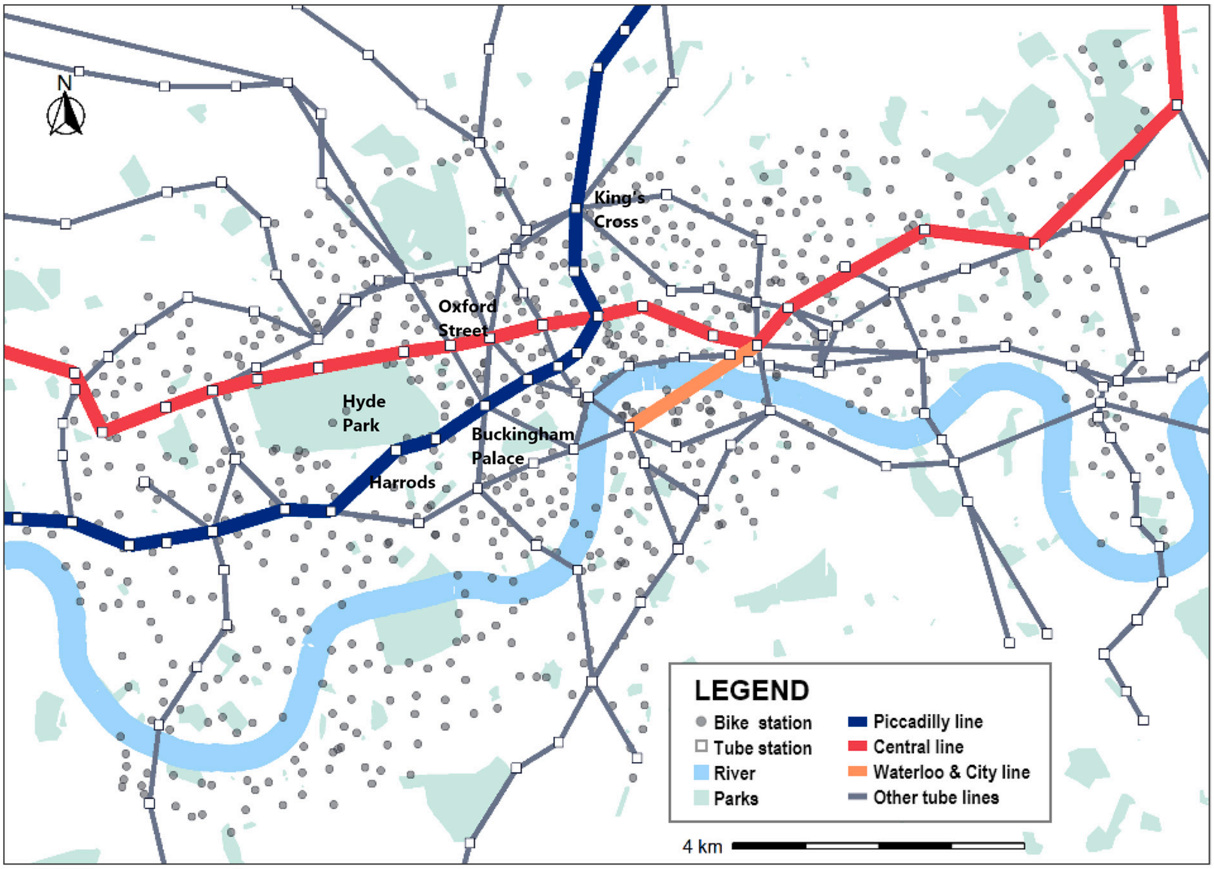

Fig. 1. London Tube Lines and bikeshare docking stations.

data, provided by the UK Consumer Data Research Centre,[1] were applied to supplement spatial coordinates for trip origins and destinations. The data describes *station-id, coordinates* and several other variables such as the docking station's *opening-date*. When linked to LCHS trip OD records by matching on *station-id*, spatial details of travel flows can be obtained.

3.2.2. Docking station availability data

Data on the availability of bike docks are obtained from the LCHS live feed.[2] This records the number of available bikes and (empty) docks at each docking station every 10 min. The variables include *station-id*, *timestamp*, *number of available-bikes* and *number of empty-docks*. Stations can sometimes lack bikes or docks due to changes in bikeshare demand throughout the day. For example, Beecham et al. (2014) revealed that many people ride bikes from their home for commuting in the morning. This renders some docking stations unavailable to users at specific periods. Examining the time-series of dock availability helps to evaluate variations in scheme "usability" during the course of the day, or in transit disruption.

3.3. Analysis

3.3.1. Spatiotemporal trip analysis

In order to shed light on when and how Tube disruptions may impact or increase bike travel, temporal analysis compares the time-series of hourly bike travel counts over the four strike days and their comparison days. Within these periods, bike trip data were also aggregated over two different spatial units to characterise ridership change and its spatial patterns. Bike trips were first aggregated over a 500 m hexagonal grid (roughly 0.6 km^2) covering the central London study area. The reason for using 500 m is that the average distance of nearby docking stations is reported as approximately 500 m (Duncan, 2015). Bike trip counts were allocated to the grid cells based on the origin station. The change in counts was determined by comparing counts from the control data (average value of 2 non-strike days for each disruption). The second approach was to aggregate bike trips over docking stations and to calculate changes (Saberi et al., 2018). Docking stations were categorised into different groups based on their shortest distance to disrupted Tube stations. A spatial interval of 250 m was used as suggested in the work of Saberi et al. (2018).

Fig. 2 shows the hexagonal grid map of the ridership on non-strike weekdays and weekends, based on the average value of the control group (non-strike days) of Strike 1 and Strike 2. On weekdays, areas in Waterloo (marked as 1 in Fig. 2 a) have the highest number of travels (more than 1100). There are also many trips around Liverpool Street Station (mark as 2) and the northeastern corner of Hyde Park (mark as 3), and the number of trips in these hexagons are between 650 and 900. In contrast, trip numbers at the weekend are relatively smaller, the highest amount is at the northeastern corner of Hyde Park (mark as 4), reaching 358. Trips are heavily concentrated around west London, Hyde park (4), also many are made in areas close to Liverpool Street Station (5), and Soho (6).

3.3.2. Docking station availability analysis

When using bikeshare schemes, travellers may encounter the problem of having no bike available at their desired trip origin, or more frustratingly, having no docks available at the desired destination. Increases in bikeshare usage, and greater competition for bikes and docks, may lead to a higher rate of such "service outages" (De Chardon et al.,

[1] https://www.cdrc.ac.uk

[2] https://tfl.gov.uk/tfl/syndication/feeds/cycle-hire/livecyclehireupdates.xml

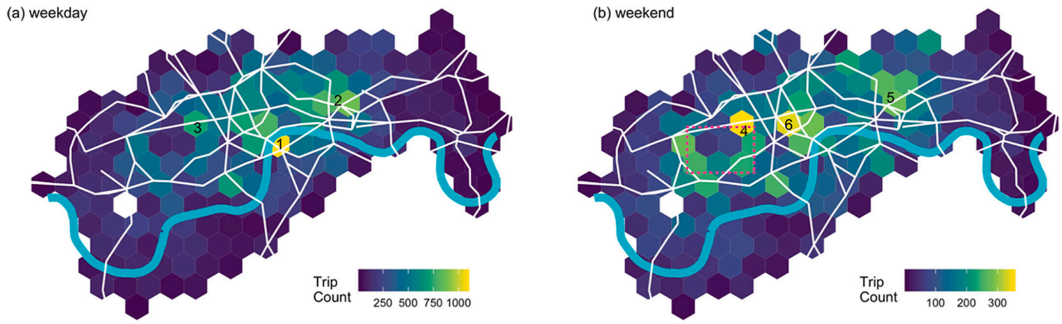

Fig. 2. Trip count on non-strike days: (a) weekday; (b) weekend.

2016), decreasing the scheme's reliability and attractiveness. During transport disruption, it is therefore especially important to ensure the availability of both bikes and docks. In LCHS, an individual station has 24 docks on average. In this work, we use a threshold of 15% to identify stations that have low availability. That is to say, if a docking station has less than 15% bikes or 15% empty docks of its total capacity, then it is marked with the status of "low availability". The proportion of 15% is an arbitrary choice; considering the typical dock capacity (24), it roughly equals to a mean value of three bikes or docks. We consider this to be a sensible threshold for our analysis.

As described in Section 3.2.2, availability data indicates the number of available bikes and docks at a frequency of ten minutes. Therefore, each station has six observations describing its status each hour. This paper defines the sum of "low availability" timestamps in each hour as a "service pressure" index, so it has a range of between zero to six. Higher values indicate that more timestamps have seen insufficient availability, whilst lower values suggest that the stations are often at a more balanced state. By analysing the fluctuation in service pressure in different groups of stations, the dynamics of the service provision can thus be evaluated, also reflecting their varying spatiotemporal patterns during strikes. The time periods of low bike usage, i.e. late night hours, were removed from the analysis due to the small number of trips made and the steady service provision at those times.

3.3.3. Graph (network) analysis

Events in Tube networks may not only impact bike ridership volumes, but also change the structure of travel patterns and flows (Saberi et al., 2018; Yang et al., 2019). To quantify these structural changes, graph-based analysis was utilised in this study. First, the travel flows in LCHS were represented as directed and weighted graphs. A graph consists of a number of nodes (i.e. vertices), and they are connected by links (i.e. edges) to indicate their relationship and interactions. Examples include social network graphs and global flight line graphs. To present LCHS as a directed and weighted graph, the bike docking stations were cast as nodes, while the cycling trips between them were defined as the links, with direction (from origin to destination) and weight (frequency) attributes. Once graphs are constructed, different indices can thus be derived to describe the state of the structure. By comparing non-strike and strike day graph indices, it is possible to characterise related structural dynamics and evolution, leading to a more comprehensive understanding of the changed relationships between OD pairs, and the different roles of docking stations. The indices can be categorised as measures for graph nodes, graph links and whole graph structure.

Node centrality measures are helpful for characterising graph nodes. They are indicators of the importance of individual vertices in a graph, and the definition of importance may vary over different indices. For example, the most common and basic node centrality is the degree. In this study, degree describes how many other bike stations in the graph are linked to a given bike station (with either in- or out-flows). There are also many other centrality measures such as flux, PageRank, node betweenness and eigenvector centrality. Eigenvector centrality (Bonacich, 2007) extends the idea of node degree by considering that nodes connected to other high centrality (degree) nodes should have a higher importance score than those connecting to low centrality nodes. It is also a relative measure, which ranges from zero to one, with higher values indicating larger importance and centrality.

Graph links can also be evaluated by various indices, with the most common being link weight. In the context of bikeshare network, link weight represents the number of bike trips (OD frequency) connecting one docking station to another.

There are also graph (global) level indices or metrics that can be used to characterise the state of the whole structure, for example, graph transitivity and assortivity. Transitivity (also called clustering coefficient), indicates the extent of graph nodes within a network cluster (i.e. community, subgroups, cliques). It captures the degree of local cluster (sub-graph) interactions compared to connections with nodes outside of the cluster (Saberi et al., 2018). It is calculated from the ratio between the observed number of closed triplets (triangles) and the maximum possible number of closed triplets in the graph structure.

Assortivity considers the preference for a graph's nodes to attach to others that are similar in centrality (Newman, 2002; Noldus and Van Mieghem, 2015). In the context of bikeshare schemes, higher values imply that similar important docking stations, such as the ones close to transit hubs, are more likely to be connected by travel flows.

The various graph metrics were calculated for the periods during each Tube strike, and compared to those calculated for non-strike days under the hypothesis that any changes in these may indicate the temporary structural responses to strike activity. Bike trips from the two comparison days were cast into two graphs, with their metrics calculated. Then the average value of the two was used for comparison. In addition to this, changes in the maps of flows were examined to confirm the findings and to provide context for interpreting the various graph metrics, thereby providing a deeper understanding of the observed trends. A particular focus was placed on OD pairs that experienced ridership increases, as these were hypothesised to represent higher transport needs. Thus, this work compares how different places are more strongly connected by LHCS users, which helps to interpret underlying travel behaviours.

4. Results

4.1. Bikeshare usage characteristics

4.1.1. Temporal pattern

A consequence of Tube strikes is an increase in bike journeys, as shown in Fig. 3. A network-level weekday disruption (Fig. 3 a) was found to increase bike trip volumes from 37,070 to 69,734 (88%) throughout the day. At the weekend (Fig. 3 b), the numbers rise from 15,910 to 24,160 (52%), with a more significant peak time around 2–3 pm.

The hourly use changes are also associated with the spatial scale of the incident. When line-level strikes occurred (Fig. 3 c, d), the increases

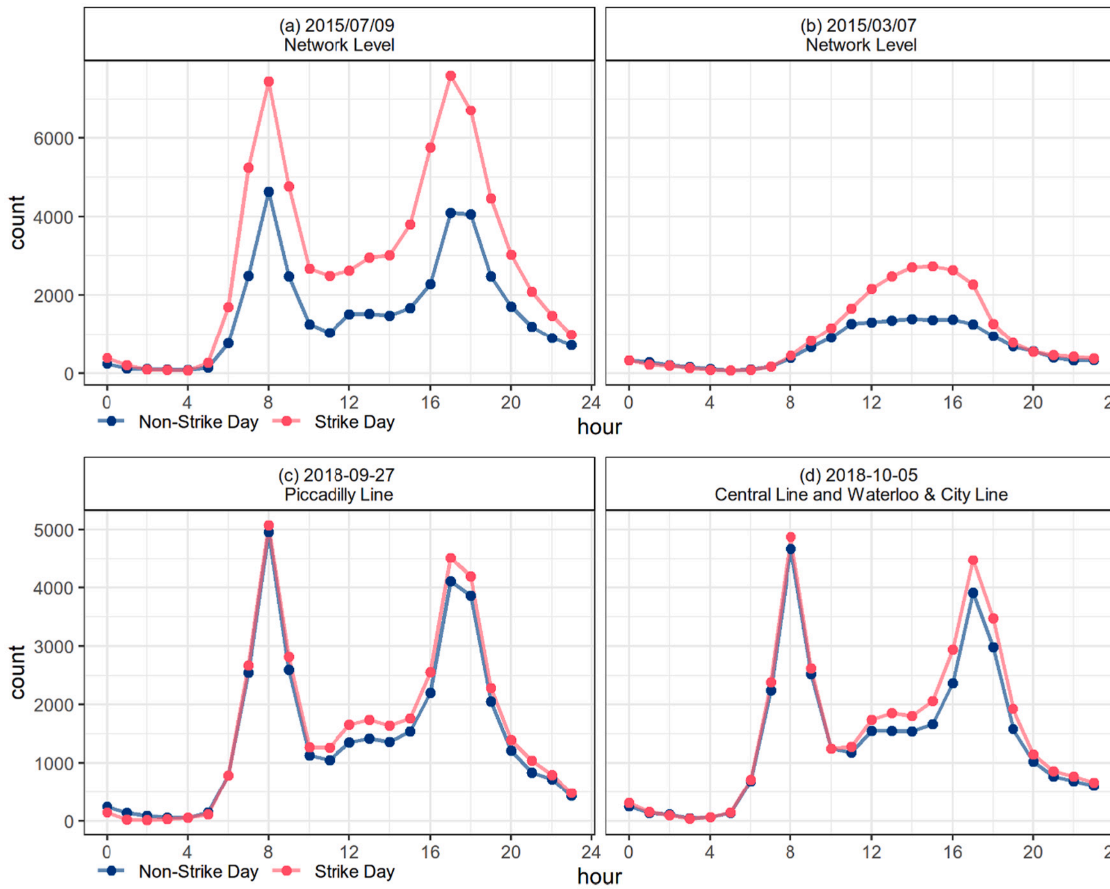

Fig. 3. Hourly LCHS bike use on strike days and non-strike days; (a) Strike 1; (b) Strike 2; (c) Strike 3; (d)Strike 4.

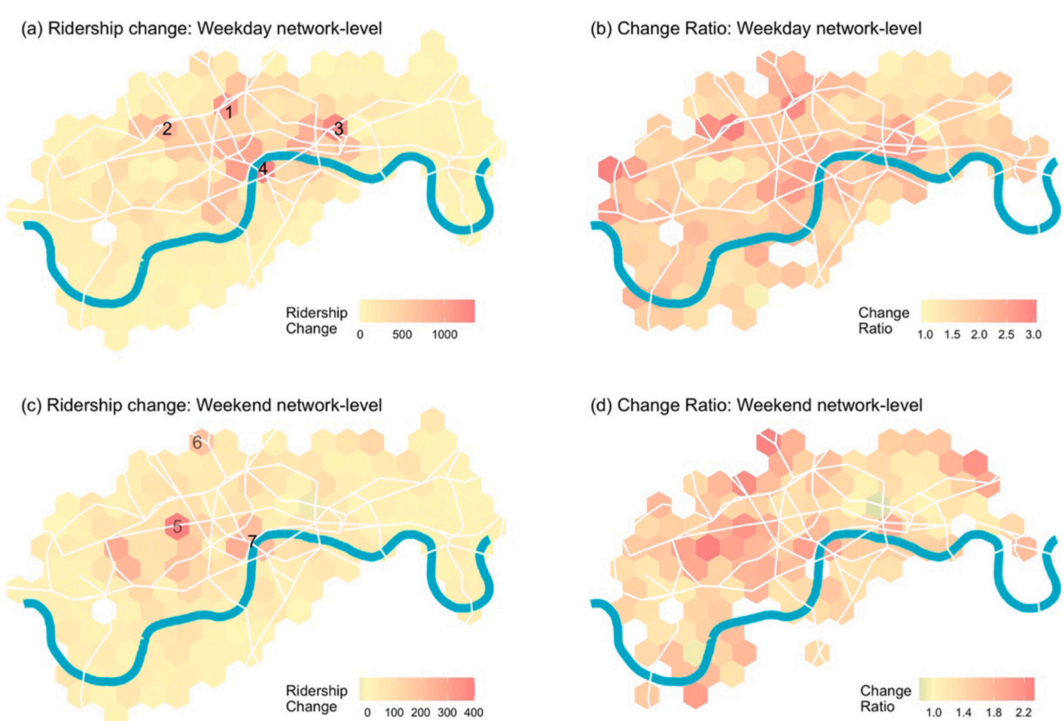

Fig. 4. Ridership change in the hexagonal grid, white lines are disrupted Tube lines; (a) Ridership change - Strike 1; (b) Change ratio – Strike 1; (c) Ridership change – Strike 2; (d) Change Ratio – Strike 2;

are less pronounced. Total use increased by 9.9% during Strike 3, and for Strike 4, it is 12.2%. The smaller increases compared to network-level strikes is to be expected and suggests that additional increases in bikeshare usage are likely to be constrained to parts of the city that fall within the disrupted line's service catchment. A more subtle but interesting pattern can also be observed: trip volumes (Fig. 3 c, d) increase from noon to 8 pm, while there is only a marginal impact on trip volumes in the morning (6–10 am). This may be due to the fact that there is generally less flexibility when travelling in the morning peak. The observational data shows that the morning peak is consistently narrower than the afternoon peak (Fig. 3 a, c, d). This has particular implications for the LCHS, where usage is heavily constrained by the number of bikes and docking spaces available. Intense competition for bikes and spaces at peak times means that the scheme can support only a limited number of additional trips – and this is exacerbated when disruption events such as Tube strikes contribute additional demand.

Overall, the different changes in patterns of hourly use indicate that network-level and line-level strikes have varied temporal impacts on people's modal shifting to bikeshare. While network-level disruptions increase trip frequencies across most time slots, line-level strikes impact noon and afternoon periods more heavily. Weekend cycling has very different trends compared to weekdays, but increases are observed particularly in the afternoon of the strike days.

4.1.2. Spatial patterns

The spatial pattern of LCHS ridership also varies during different Tube strikes, as illustrated in Figs. 4 and 5. Fig. 4 (a,c) and Fig. 5 (a, c) show the changes in trip count in hexagonal grids; while Fig. 4 (b, d) and Fig. 5 (b, d) presents the relative change, which is the change ratio, and it is calculated as:

$$Change\ Ratio = \frac{T_s}{T_N}$$

Where T_s is the trip volume on the strike day, and T_N is the average volume of trip count on non-strike days (the control group). Because T_N may be very small in some regions, using a small number as the denominator to calculate the relative change can lead to calculation and sensitivity problems. Therefore, a relatively arbitrary threshold for T_N is usually set in calculating the relative change in literature (Yang et al., 2020). In this work, the threshold is set to 50.

Trip volume significantly increased in central London during Strike 1 (Fig. 4 a), with areas surrounding train stations experiencing the largest increases. For example, King's Cross, Paddington, Liverpool Street and Waterloo train station (marked as 1, 2, 3, 4 in Fig. 4 a). The change ratio was also found to be higher in King's Cross and Paddington. In contrast, during a weekend strike, areas with the highest number of increases are around Hyde park, especially the northeastern corner (marked as 5 in Fig. 4 b). Waterloo and Piccadilly Circus (7) and Regent's Park (6) also have higher ridership and change ratios. Some hexagons at the periphery have a high value in change ratio. This is due to the small denominator (T_N) in these regions, and they are more sensitive to the changes in ridership. Overall, these varied patterns suggest that the spatial distribution of increases in bike use is severely impacted by whether the strike occurred during a weekday or weekend.

For line-level strikes (Fig. 5), the impact is more localised, with regions closer to disrupted lines experiencing increases in use. In Fig. 5 (a, b), areas closest to south Kensington (marked as 1) and Knightsbridge (2), where numerous museums are located, show the greatest increase in bike use. Green park (3) and Piccadilly Circus (4) also show marked increases. The change ratios in west London are generally higher. During Strike 4 (Fig. 5 c, d), most regions along the Central line experienced higher LCHS trip counts and change ratios.

The relationship between bike docking stations' distance to Tube and bike use changes is examined by boxplots in Fig. 6. The x-axis indicates the distance to the nearest disrupted Tube stations, and the y-axis shows changes in trip frequencies at those docking stations (Saberi et al., 2018). A distance decay pattern can be observed during weekday disruptions (e.g. Fig. 4 a, d), with bikeshare stations closer to Tube stations experiencing a greater increase in use, and these increases reducing with distance to affected Tube stations. This is consistent with the findings of

Fig. 5. Ridership change in the hexagonal grid, white lines are disrupted Tube lines; (a) Ridership change - Strike 3; (b) Change ratio – Strike 3; (c) Ridership change – Strike 4; (d) Change Ratio – Strike 4.

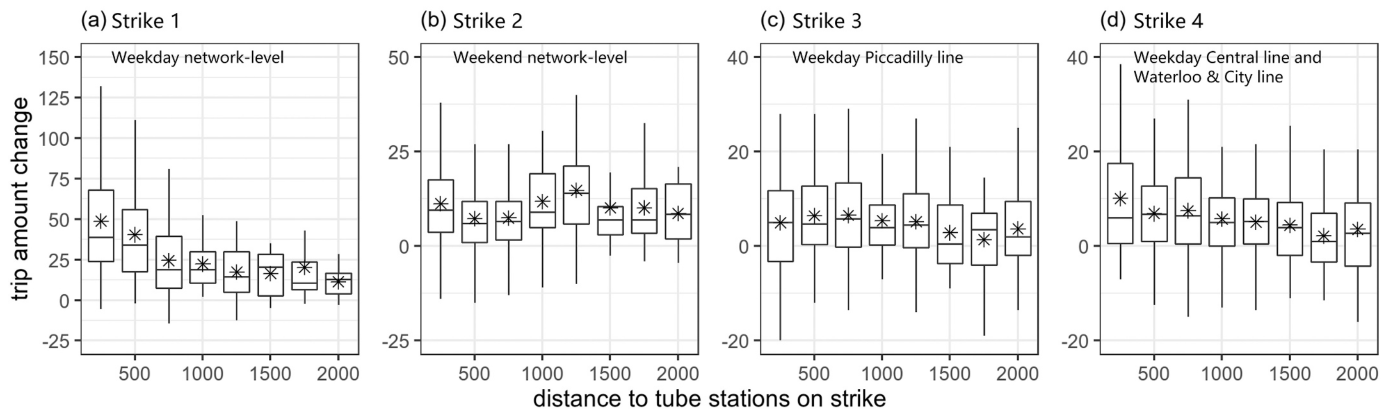

Fig. 6. Box plots of bike use changes with distance to the nearest Tube stations affected by disruption; (a) Strike 1; (b) Strike 2; (c) Strike 3; (4) Strike 4.

Saberi et al. (2018). However, for weekend strikes (Fig. 4 b), the pattern is not replicated; rather increases are observed at greater distances with the peak at 1000–1250 m from the disrupted Tube stations. The differing patterns of distance decay may be driven by cycling purposes. On weekdays, bike use is more heavily associated with utility cycling (commuting), whilst weekend trips are more likely to be discretionary and made for leisure purposes. This inference can be further supported by comparing line-level strikes and associated trips. During Strike 4 (Fig. 6 d), the distance decay trend is more similar to Strike 1 (Fig. 6 a); whilst in Strike 3, no (or a less) obvious distance decay exists. Tube lines affected by Strike 4 run through many employment-related locations and are associated with many cycling trips for commuting purposes. By contrast, The Piccadilly line, affected in Strike 3, covers comparatively more tourist attractions than Central and Waterloo & City (Strike 4). So utilitarian commuting trips are less displaced in Strike 3, as shown by a lack of distance decay in Fig. 6 (c). A further interesting pattern is observed in line-level strikes (Fig. 6 c, d). There is an increase in trip frequencies for the most distant group (2000 m). This may be observed due to displaced Tube travellers switching to other travel options (e.g. overland local train services, buses, etc.) combined with bike travel for their journey, thereby contributing to more bike trips in typically less-heavily used parts of the LCHS network (Larcom et al., 2017). This phenomenon and related route changing behaviour is further analysed in later sections (Sections 4.3 and 4.4).

4.2. Changes in docking station availability

The increased trip volumes during strikes pose challenges for service provision. Time-series of "service pressure" measures during network-level strikes are shown in Fig. 7. This shows the frequency with which stations suffer from "low availability" throughout the day.

For weekend strikes, the number of stations recorded as under pressure doubles during the weekday morning peak (8 to 10 am). Increased competition for bikes creates availability problems for the scheme as a whole. Service pressure at weekends also increases under strike events but in a different way to the weekday strikes, with a peak observed around 16:00 (Fig. 7 b) during the disruption.

Line-level strikes lead to more localised trip increases, thereby bringing generally more service pressures to LCHS. Fig. 8 shows service pressure around specific Tube lines in the event of network- and line-level Tube strikes on weekdays. When line-level strikes occur (Fig. 8 b, d), all distance groups generally show higher service pressure in the morning, but for evening periods (e.g. around 6 pm), bike stations further from the affected Tube lines (750–1000 m) do not exhibit such higher pressure.

The results from the service pressure analysis – characterising where, when and to what extent docking stations become unusable on strike days – could inform future targeting of rebalancing strategies. It should also be noted that disruption events may counter-intuitively lead to patterns of usage that are beneficial to fleet management. There is evidence that usage under strike conditions can become more heterogeneous. Analysing the dynamics in LCHS usage in greater spatial detail may therefore be instructive, and in the following section we present such an analysis, considering full OD flow data.

4.3. Graph statistics

Different graph statistics are derived from the full LCHS OD trip data,

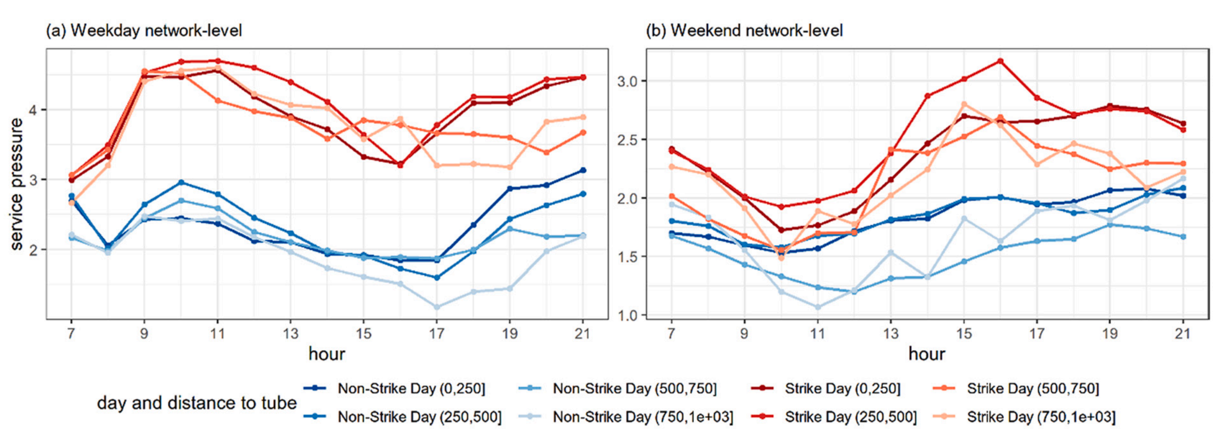

Fig. 7. Time-series of service pressure during network-level Tube strikes, blue lines indicate non-strike day, red lines represent strike day; (a) Strike 1, weekday; (b) Strike 2, weekend. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

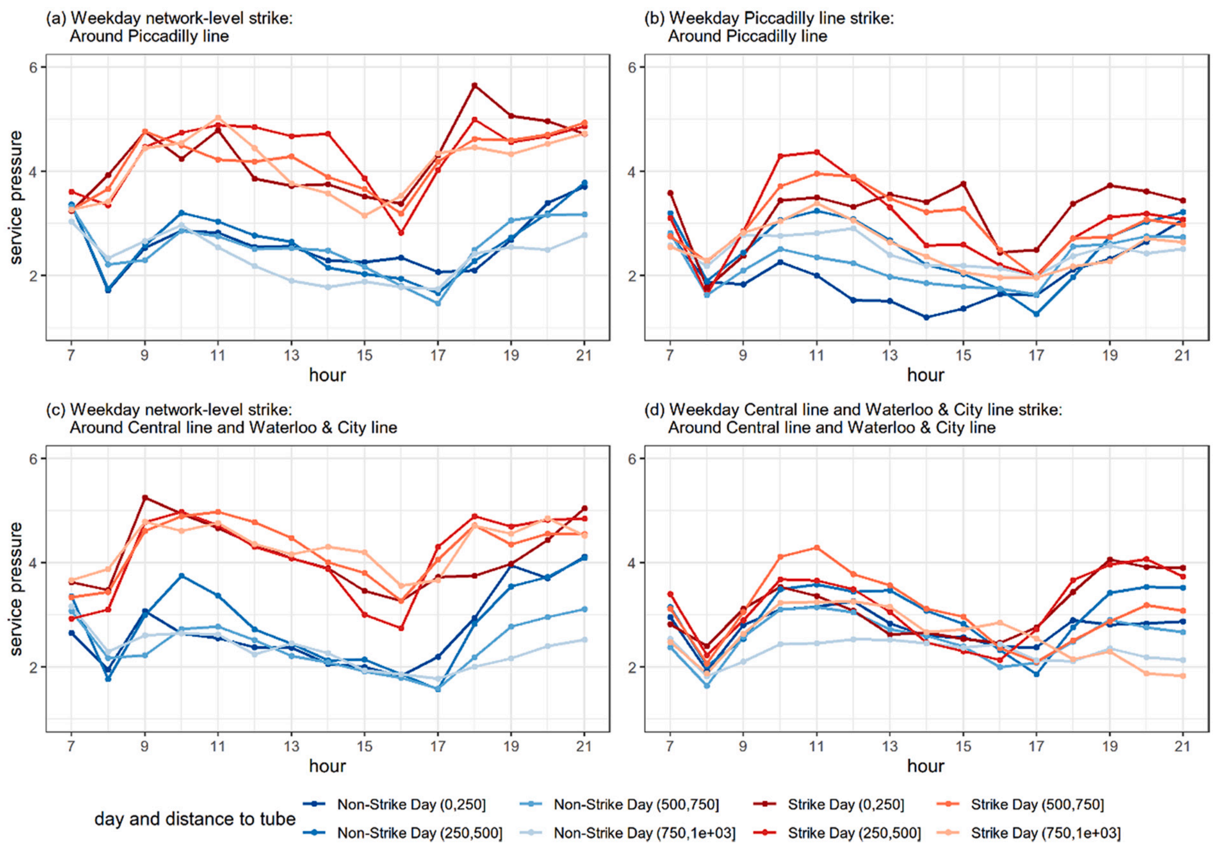

Fig. 8. Time-series of service pressure in service catchment of specific Tube lines; (a) Piccadilly line - Strike 1 (b) Piccadilly line - Strike 3; (c) Central line and Waterloo & City line - Strike 1; (d) Central line and Waterloo & City line -Strike 4.

providing various insights into changes in spatial travel behaviours under disruption. Table 2 presents these statistics from network-level strikes along with what would be expected under normal conditions (a control group). Disruptions lead to higher graph connectivity (δ),which indicates more heterogeneous cycling behaviours - new OD pairs. The number of new OD pairs (L) increased by 80% for the weekday and 38% for weekend strike events. On the one hand, this greater diversity in cycling behaviour may indicate that a wider and new set of users are attracted to the scheme during strike days. On the other hand, it is perhaps a function of parts of the scheme under service pressure becoming partially unavailable at peak times under strike conditions (established in Section 4.2), and so existing users must find alternative routes; new OD pairs are introduced by bikeshare cyclists forced to use second- or third- preference docking stations due to the additional competition for bikes/spaces during strikes.

Differences in centrality scores are also observed under strike events. Average node degree, $\overline{d}$, is larger under both events, implying that docking stations are linked to a larger set of other stations. But the co-efficient of variation in node degree, *cv(d)*, shows a contrasting pattern. Whilst the indicator remained unchanged for the weekend strike, *cv(d)* increased from 0.62 to 0.68 for the weekday strike. The reasons are twofold: (1) during weekday disruptions, where commuting and utility cycling tends to be the dominant trip purpose, demand is concentrated at particular space-times. Because of increased service pressure, some bikeshare cyclists are required to use alternative docking stations either to pick-up or drop-off bikes in intense demand regions. This will link many more nodes to one vertice; (2) and more importantly, due to the dominant commuting behaviours, parts of the bikeshare network connecting key employment centres and transit hubs (e.g. King's Cross) experience disproportionally more trip frequencies and therefore serve a more diverse set of stations than other parts of the city that are less strategically important. During weekends, however, trip purposes are typically discretionary. There may be an overall increase in LCHS usage, but this is not so spatially concentrated, so the *cv(d)* remains unchanged.

Average link weight, $\overline{w}$ increases as a result of more trips being made, but the coefficient of variation, *cv(w)*, shows an interesting opposite pattern. The value of *cv(w)* decreased under weekday strike while it increased under the weekend strike. Combining this pattern with the larger $\overline{w}$ in Strike 2 than Strike 1, a speculative explanation can be proposed: many of the new flows (OD pairs) occurring under weekday disruptions are of comparatively lesser weight than those occurring during the weekend strike event. It is likely that the new weekday pairs

Table 2
Graph Statistics of network-level strikes.

Graph Property	Strike 1 (weekday)	Strike 1 control group	Strike 2 (weekend)	Strike 2 control group
N	735	739	742	740
L	50,455	28,027	16,474	11,973
L/N	68.6	38	22.2	16.2
$\overline{d}$	137.3	75.9	44.4	32.3
cv(d)	0.68	0.62	0.63	0.63
$\overline{w}$	1.38	1.32	1.47	1.32
cv(w)	0.80	0.98	1.27	0.84
δ	0.187	0.103	0.06	0.044
T	69,734	37,070	24,160	15,910
a	0.001	0.098	0.071	0.069
t	0.31	0.23	0.17	0.14

N represent number of nodes; L is the number of links; $\overline{d}$ is the average node degree, cv(d) is the cofficient of variabtion of node degree; $\overline{w}$ is the mean link weight; $\delta = 2\ L/N^2$ is defined as network connectivity; T is the sum of all link weights; a is the graph assortativity; t is the transitivity.

are between alternative or less-popular docking stations – made by commuting cyclists who are not able to complete their preferred trip (OD pair) due to the additional and highly concentrated demand. Further evidence to support this assumption is in the graph assortivity scores (a). For strike 1, assortivity shows an exponential reduction from 0.098 to 0.001. In contrast, under Strike 2, assortivity slightly increased (by 0.002). This difference indicates that under weekday disruptions, it is more common to observe bike trips between an important, heavily used hub docking station and another, previously underused docking station; and by extension that weekday strikes induce new trip combinations (OD pairs) and possibly new users. In contrast, assortivity increased slightly under weekend strikes, suggesting that these more discretionary trips tend to be made typically between similarly important (popular) docking stations.

Overall, both Strike 1 and 2 have contributed to a denser cycling network, with a larger number of travel OD pairs and increased average link weights – a function of greater LCHS use during strike events. However, due to different travel purposes and docking station availability, the weekday strike (Strike 1) makes the graph structure more heterogeneous in terms of node centrality (degree), while the weekend strike (Strike 2) does not.

Further analysis on node centrality is shown in Fig. 9, and illustrates the CDF (Cumulative Distribution Function) of degree and eigenvector centrality. A high node degree indicates a node is connected to many other nodes, while a high eigenvector score means that a node is connected to many other nodes, which are also high in centrality (Oldham et al., 2019). All CDFs in Fig. 7 follow a power law. Fig. 7 (a,b) suggests there is a higher probability of observing a node (a docking station) with a larger degree (connects to many other stations) during strikes on both weekdays and weekends, this accords with the patterns of $\overline{d}$ in Table 2. Interestingly, Fig. 9 (c,d) shows a diverging pattern in eigenvector centrality: in Fig. 9 (c) there is a large difference between non-strike and strike days, while in Fig. 9 (d) no such difference exists. This further reinforces the patterns previously identified. When a low degree node links to a high degree node – a frequently used docking station connects to a less frequently used docking station – the eigenvector score of the low node (the less frequently used docking station) will increase. This kind of situation is more common in Strike 1, as indicated by the assortivity changes in Table 2. During a weekend strike, however, docking stations are more likely to link to other docking stations with similar centrality. Therefore, many low-scoring nodes do not link and benefit from other high centrality nodes – during weekend strike events, there is a 'doubling-down' on existing travel behaviours with increased trips between already frequently used docking stations, presenting a "rich-club" effect (Zhou and Mondragón, 2004).

Strikes 3 and 4 are line-level strikes, which also happened on weekdays. Therefore, the changed graph statistics (Table 3) share many similar trends with Strike 1. For example, higher $\overline{d}$ and $\overline{w}$ have been

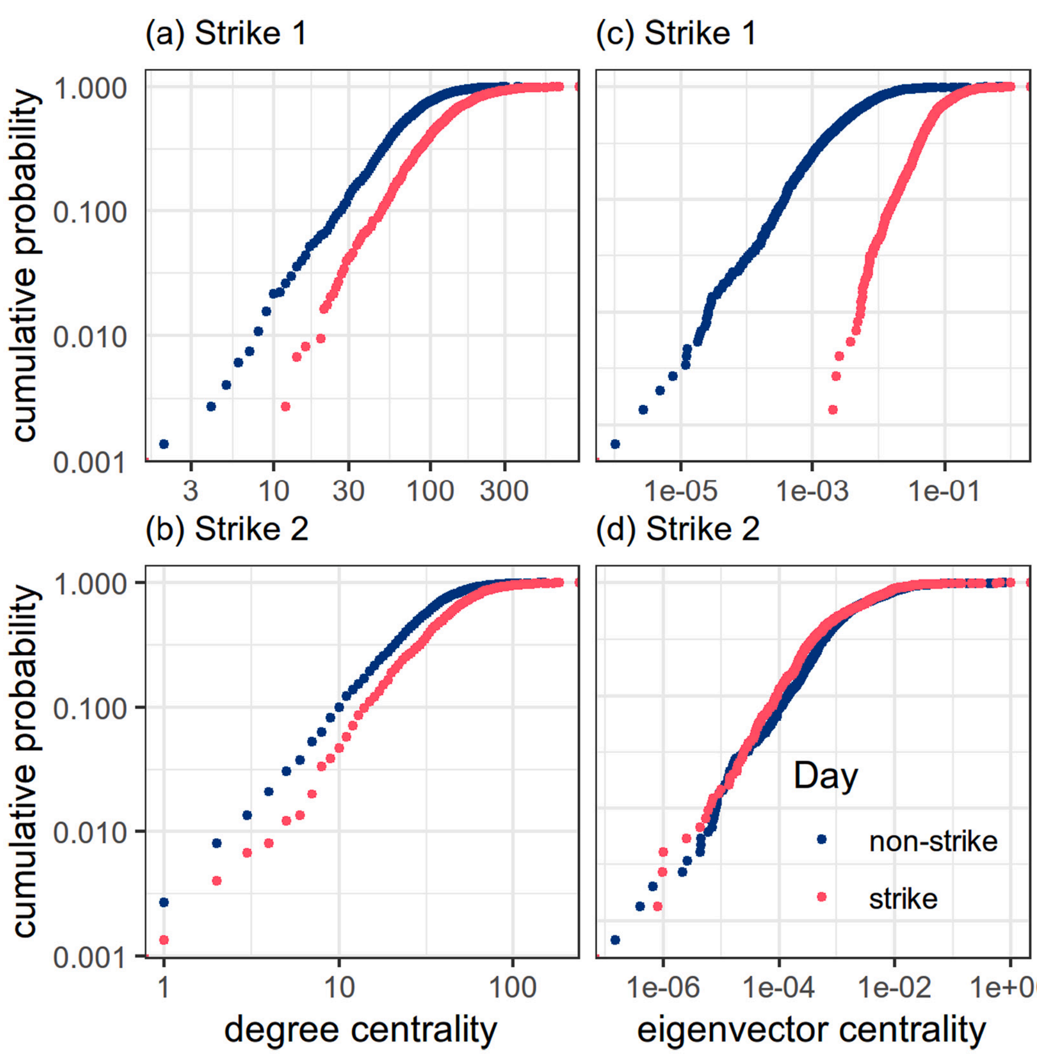

Fig. 9. Node centrality change in network-level Tube strikes; (a) Strike 1: degree; (b) Strike 2: degree; (c) Strike 1: eigenvector centrality; (d) Strike 2: eigenvector centrality.

observed in Strike 1, 3 and 4. But a different pattern can be identified in *cv(w)*. While strike 1 (network-level) shows a lower value, decreasing from 0.98 to 0.8 (Table 2), strike 3 and 4 both show increases in this index (Table 3), and is due to the effect of changing Tube routes. For example, in the evening peak, when all Tube lines are unavailable (Strike 1), commuters may cycle a long distance directly from their workplace to home/train station. Due to the large variance in work-home/train station location pairs, the bike travel flows will present higher randomness to connect different docking stations. Hence, higher homogeneous link weights may be observed, and lead to lower *cv(w)*. When only certain Tube lines are affected (Strike 3,4), people may change their Tube route, and combine it with a shorter bikeshare journey to their destination. In this case, the cycling origin/destination randomness is lower than Strike 1 because many bike trips are aggregated at (made from/to) certain docking stations close to unaffected Tube lines.

To obtain a more comprehensive understanding, and to confirm the changed travel behaviours as speculated here as well as in Section 4.1.2, the next part provides a supplementary analysis using flow maps.

4.4. Origin-destination visualizations

Whilst the graph statistics provide useful aggregate-level summaries, visual analysis of the OD flow data allows us to characterise with greater richness the nature of changes in response to the strike events.

In Figs. 10 and 11, cycled OD pairs are represented as curves, coloured with a gradient to indicate journey direction, with a yellow end representing journey origin and a red end indicating journey destination (Beecham et al., 2014). Flows are encoded according to the increases in flow frequencies recorded during network-level strikes (Strike 1 and 2) using curve width. To improve the readability of the flowmaps, only major increases, namely the flows with a frequency of 5 or higher, are presented in Figs. 10 and 11. During Strike 1 (weekday), increased trip frequencies are distributed across central London and the City of London. London's large transit hubs can also be identified here. For example, increased trips are made to depart from or arrive at King's Cross, Liverpool Street, Paddington and Waterloo.

For Strike 2 (weekend), a different pattern is identified. There is a sense that bikeshare users "double down" on their typical weekend travel behaviour - increases are observed for apparently leisure trips made within Hyde Park and West London. There is also a stronger bi-directional link between the southeast corner of Hyde Park and Piccadilly Circus, which are close to major shopping and entertainment areas in London's West End. Higher trip counts around Regent's park can also be identified. One of the most substantial increases in trip frequencies runs through the northeast and connects Victoria Park and the Broadway Market, and there are some comparatively long distance journeys from docking stations aound Liverpool Street and Millwall Park. Overall, the increased OD pairs typically connect one leisure or shopping spot to another.

Table 3
Graph Statistics of line level strikes on weekday; Strike 3: Piccadilly Line; Strike 4: Central Line and Waterloo & City Line.

Graph Property	Strike 3 (Weekday)	Strike 3 Control group	Strike 4 (Weekday)	Strike 4 Control group
N	784	785	785	784
L	29,569	27,207	28,588	25,932
L/N	37.7	34.7	36.4	33.1
$\overline{d}$	75.4	69.3	72.8	66.1
$cv(d)$	0.64	0.65	0.64	0.64
$\overline{w}$	1.28	1.27	1.3	1.28
$cv(w)$	0.74	0.64	0.68	0.65
δ	0.096	0.088	0.093	0.084
T	38,321	34,883	37,648	33,562
a	0.092	0.096	0.09	0.098
t	0.22	0.21	0.21	0.2

Fig. 11 illustrates weekday line-level Tube strikes, and some differences to network-level disruptions (Fig. 10 a) can be found. Many major links in Fig. 10 (a) disappeared in Fig. 11. For example, in the case of train transfer, the stronger flow from Paddington to King's Cross station (Fig. 10 a) is not visible in Fig. 11 (a); instead, many more trips are observed connecting King's Cross and locations close to Tube line (e.g. Bakerloo line and Central line) stations in central London and the City of London. This phenomenon strongly implies the change of Tube routes among travellers. When all Tube services are unavailable, people may cycle from Paddington to King's Cross to transfer trains, while if only Piccadilly line is in disruption, transit users will firstly travel via other Tube lines to stations that are close to King's Cross, then combine a bike trip to reach their destination (King's Cross). This highlights the role of cycle hire as a flexible travel mode, and its advantages in providing a service under different conditions for travellers to complete their journey, and strengthen urban and mass transit resilience.

5. Discussion

Several findings can be abstracted from this analysis. Firstly, the effect of public transit disruptions such as Tube strikes on bikeshare usage clearly varies depending on the nature of the public transit disruption. A network-level strike will increase overall bike trip frequencies throughout the day, whilst line-level disruption leads to higher usage mainly in the afternoons. There is also an expected distance decay effect to these increased trip frequencies, with docking stations closer to the disrupted Tube lines experiencing the largest increases in trip frequencies during the strike events. This is consistent with other observational studies (Saberi et al., 2018), but we add that this distance decay effect is much stronger where the tube strike events occur in parts of the city that typically serve commuting journeys. The distance decay effect is much reduced, or even disappears entirely, for parts of the city or time periods that are associated with leisure activities.

Secondly, the consequences of increased bikeshare usage on the LCHS's usability is quantified by creating a novel service pressure index. Tube strikes are found to increase service pressure and the likelihood of docking stations either containing insufficient available bikes or docks. The consequences are most severe for weekday network-level strikes – the number of observed instances of docking stations under pressure generally doubles when compared to the non-strike control. For line-level strikes, the patterns of increased service pressure vary depending on the proximity of a docking station to the disrupted Tube stations.

Thirdly, graph-based analysis has identified several trends. The results indicate that Tube strikes can lead to a denser cycling network with higher numbers of trips and graph links. But weekday strikes tend to link nodes (bike docking stations) with varied centrality scores, and this is opposite to weekend disruption events when slightly more nodes with similar centrality are connected. These opposing patterns relate not only to differences in travel purpose (commute versus leisure), but also differences in observed service pressure during weekday and weekend disruption events. Moreover, visually representing changes in trip patterns via flow maps is instructive, with increased bikeshare trips connecting central London with major rail terminals, suggesting that bikeshare is being substituted for (commuting) journeys that would otherwise be taken by Tube. These all imply the importance and potential of bikeshare as a flexible travel mode that might therefore strengthen urban transit resilience.

Whilst the LCHS is demonstrated to provide an alternative travel option when other parts of the transit network are under disruption, the scheme soon reaches capacity, especially at peak times. Efforts to maintain a functioning bikeshare network under disruption events may have important social benefits – providing a cheap and accessible travel alternative, especially to lower-income groups whose employment may be more precarious, shift-based and less flexible (Green et al., 2012; Zhu

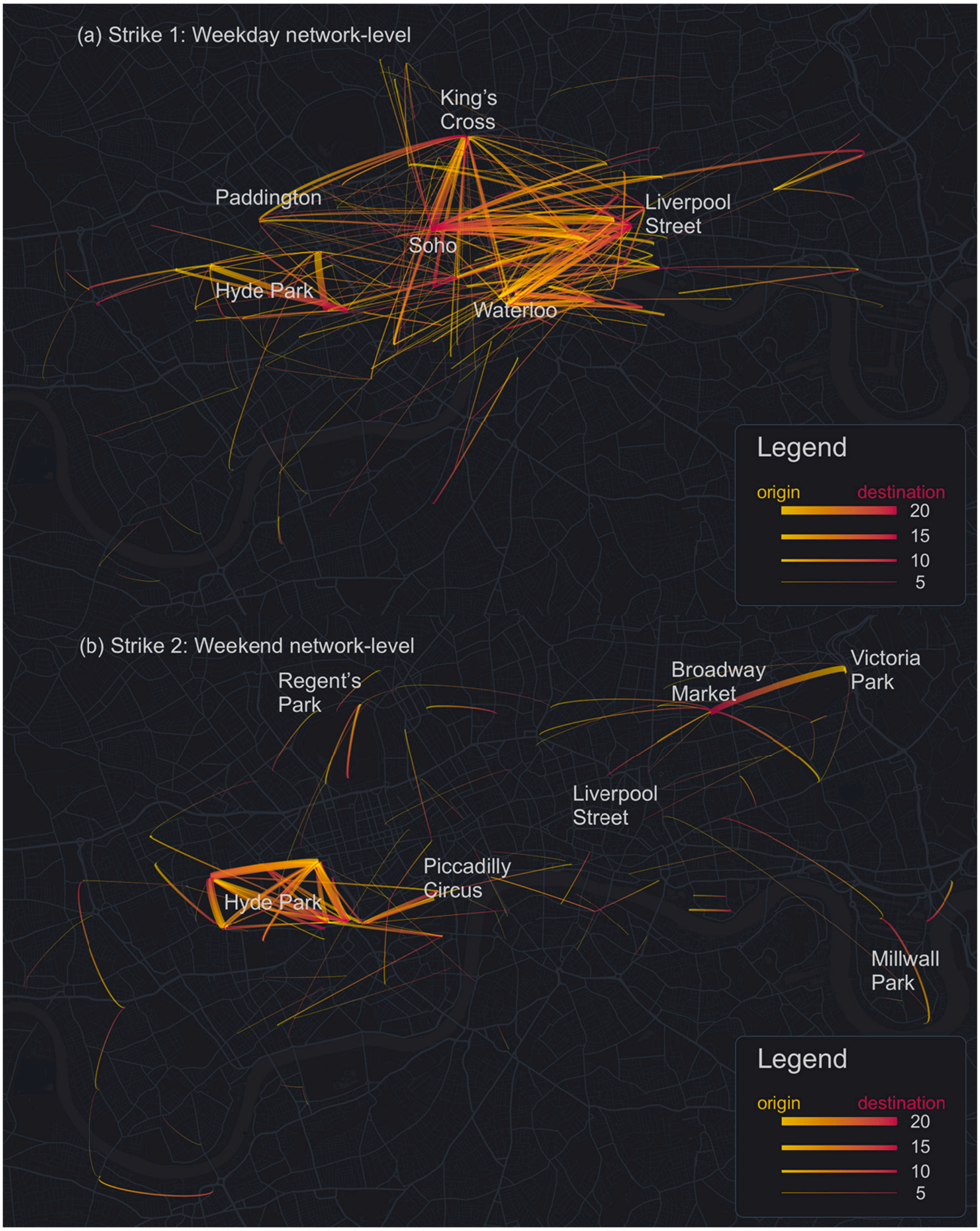

Fig. 10. Increased OD flows during network-level Tube strike; (a) Strike 1; (b) Strike 2.

et al., 2017; Younes et al., 2019). The maintenance and bike fleet rebalancing work should take the impacted behaviours of travellers into consideration. For example, when line-level disruptions happen, it is also important to provide more cycles around unaffected Tube lines, because they will experience higher demand due to travellers' changing Tube routes. Pop-up cycle lines may be set up between different hotspots locations as identified in this work. It helps to enlarge the space to meet the temporary increased cycling activities, provide a safer environment and eliminate potential congestion on cycle lanes.

Disruptions and reduced capacity in other public transport will lead to higher usage of bikeshare, and these might be developed as new travel habits for people. The social distancing guidance may lead to much higher LCHS usage, combining with the increasing popularity of sustainable travel mode, more investment into LCHS, and improved service management and station capacity are required to meet the potential demand. This also helps to promote and facilitate greener and healthier travel of people.

The results in this work are derived from analysing bike sharing data under the context of temporary public transit disruptions. But they also help to guide some long-term strategy directions to support sustainable travel mode in the future. The UK government has set its path to net-zero transport (2050), and the strategic priorities for transport

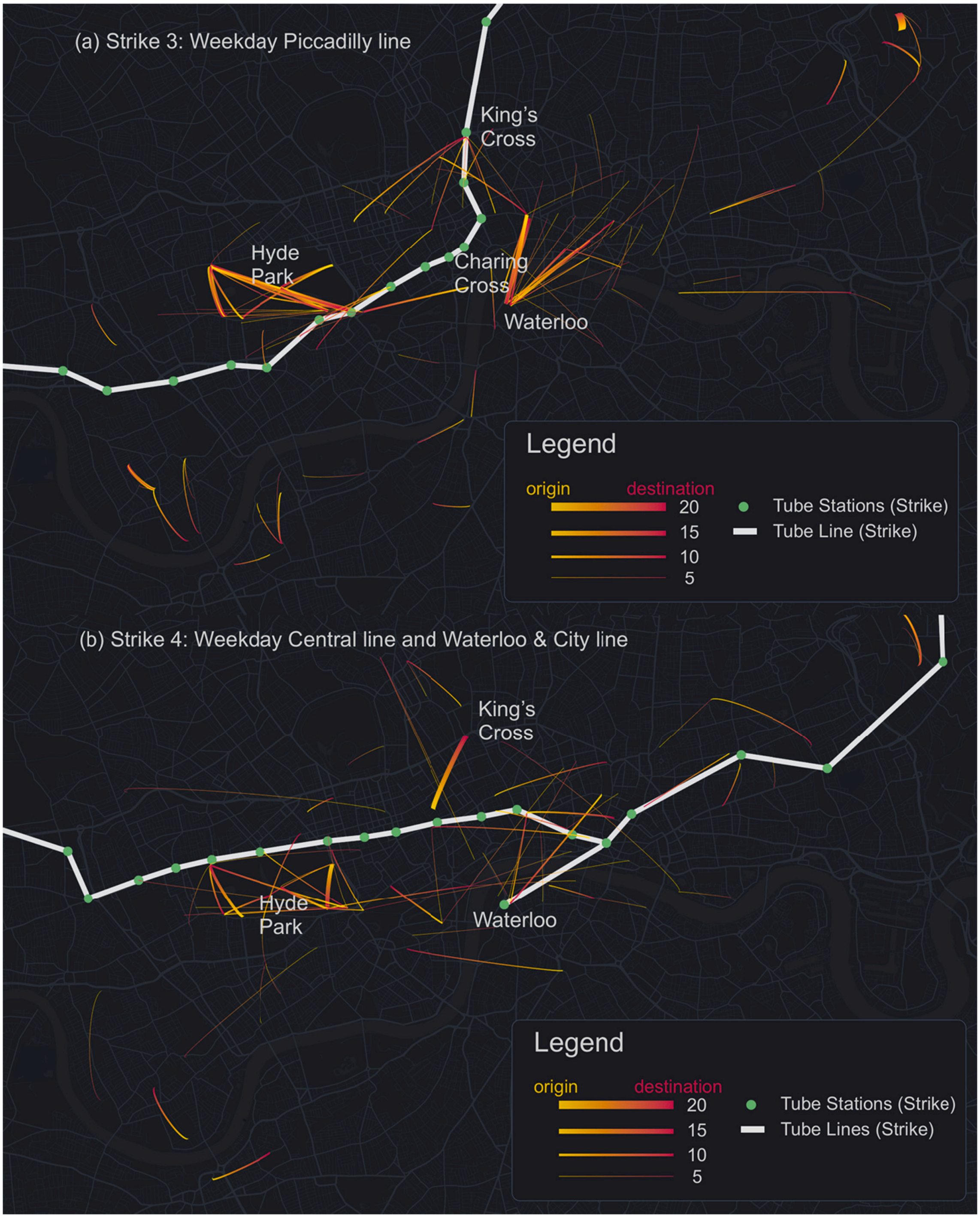

Fig. 11. Increased OD flows during line-level Tube strike; (a) Strike 3; (b) Strike 4.

decarbonisation include "Accelerating modal shift to public and active transport" (Department of Transport, 2021). Public transport and active travel will be the natural first choice for daily activities in the future (Department for Transport, 2021). Therefore, a cohesive, widely available and resilient net-zero transport network is the key to achieving this. It is important to consider how the bike-sharing system might better fit the existing public transport system and help fill various transit gaps caused by temporary incidents such as infrastructure maintenance, social events, and pandemic. In addition, better cycling facilities, safer cycling routes, broader coverage of cycle hire service areas, higher density/capacity of bike parks and docking stations will make it easier for people to use cycle hire schemes (Department of Transport, 2021).

The UK government also aimed to increase active travel modes such that cycling and walking account for at least half of all journeys made in towns and cities by 2030 (Department of Transport, 2021). In the context of Tube disruptions, people are "forced" to use alternative travel modes, and the newly observed travel behaviours (new OD pairs) capture some additional structure around the geography of demand. Therefore, understanding the behaviours during various pubic transit disruptions, for example, road closure, major congestion, not limiting to Tube strike, may help direct infrastructure planning activity. In a sense, the result of "forcing" more people to use alternative sustainable travel modes (e.g. Tube strike) might be similar to "encouraging" people to use active travel (in the future). Uncovering and interpreting the changed behaviour, especially the geography of increased trips, will be vital for planning, stimulating and matching future demand with cycling infrastructure.

A shortcoming of this work is the lack of demographic and socio-economic information on bikeshare users. Some studies (Green et al., 2012; Zhu et al., 2017) have suggested that low-income groups may benefit more from bikeshare during mass transit failure, also more occasional users have seen using the sharing bikes. Therefore, future research will examine the characteristics of different groups of users and compare their modal shift behaviours. Surveys will also be used to confirm the trip purpose during varied strike events, to gauge their attitude and preferences on using bikes as an alternative travel mode. In the analysis, we speculated that new users might have been introduced to the scheme through the strike events. Decreases in the assortivity scores during weekday strikes implied new, or non-standard, OD trip pairs were being made in larger numbers. To validate this, further examination of assortivity scores immediately post-strike (residual effect) will allow more insights to be obtained. In Section 3.3.1, this work aggregated ridership in hexagonal gird cells with a length of the side of 500 m. The choice of size is relatively arbitrary and based on the fact that the average distance between bike share stations is roughly 500 m. Because bike stations are not evenly distributed, this approach may lead to cells in the city centre have more stations, while cells at the fringe contain few or no stations. To address the problem and avoid creating misleading interpretations on the result, we have carefully generated and examined other maps and statistics (e.g. change ratio, individual station-level flowmap) to supplement the analysis drawn from the grid map.

6. Conclusion

This work combined spatiotemporal analysis and graph-based approaches to explore the changing behaviour of bikeshare users in the LCHS as a result of four Tube strikes. Changes in user cycling activities and of bikeshare usability (the availability of bikes and docking points) were quantified. This study demonstrates that there is a distinct geography to affected travel behaviours and ridership that is consistent with previous studies (Saberi et al., 2018), with the pattern conditional on whether the disrupted parts of the city and the time periods relate to commuting activities. Systematic changes in travel behaviour were found by examining changes in OD flow graph structures. The observed variation in bikeshare usage under disruption events demonstrates the flexibility of cycle hire schemes and their potential for enhancing urban transit resilience. The findings of this work and the methods used provide useful information and tools for scheme operators to better manage system resources and to support cycle infrastructure policy-makers and planners in designing interventions aimed at incentivising cycling.

Declaration of Competing Interest

None.

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