Transportation Research Part A 199 (2025) 104603

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Disruptions as catalysts to sustainability? Long-term responses in bike-sharing demand to disruptions during the pandemic

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ARTICLE INFO

Keywords:
Bike-sharing
Disruption
COVID-19
Long-term impact
Resilience
Post-pandemic era

ABSTRACT

Understanding the implications of large-scale, prolonged disruptions on travel demand is important for informing the future design of resilient, efficient, and sustainable transport systems. Major disruptions during the COVID-19 pandemic provide an opportunity to shed light on this issue. While contemporaneous responses in such demand amidst these disruptions have been well documented, insights into long-term post-disruption responses remain limited. This research gap challenges the development of a transport policy agenda capable of adapting to and mitigating the enduring consequences of disruptions. This research contributes to this topic by scrutinising long-term responses in bike-sharing demand to major disruptions during the pandemic. It investigates (1) the characteristics of these long-term responses; (2) the discrepancies between the long-term and contemporaneous responses to these disruptions; and (3) the associations of the long-term responses with docking stations' contextual characteristics. We use 57-month bike-sharing demand data from London, spanning the pre-, amidst-, and post-disruption phases. Utilising pre-disruption data as a baseline and data in subsequent phases as comparisons, we apply Bayesian time-series models for counterfactual analysis to assess bike-sharing demand's responses.

We find that major disruptions during the pandemic contribute, in the long term, to a more than 20% rise in bike-sharing demand in the post-disruption phase, compared to a counterfactual scenario absent such disruptions. The increase in off-peak hour demand is greater than in peak hour demand. Demand for short- and medium-duration trips increases, whilst that for long-duration trips decreases slightly. However, despite the overall increase in demand post-disruption, the magnitude of this increase flattens over time. Moreover, bike-sharing demand's long-term responses surpass its contemporaneous responses. Finally, docking stations located in areas with a more diverse land-use mix, higher intersection density, better accessibility to public transport, and a lower percentage of minority population show a larger long-term response in demand. Our findings remain robust while accounting for the confounding impacts of COVID-19 cases post-disruption and the implementation of active travel interventions during the pandemic. We suggest that prolonged disruptions like those during the pandemic may have functioned as

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https://doi.org/10.1016/j.tra.2025.104603
Received 18 June 2024; Received in revised form 20 May 2025; Accepted 6 July 2025
Available online 22 July 2025

catalysts for the uptake of sustainable transport, such as bike-sharing. Yet, our evidence of a diminishing long-term response over time underscores a need for persistent, proactive actions to support sustainable transport after disruptions subside, if the positive response is to be sustained.

1. Background

Insights into the implications of large-scale, prolonged disruptions on transport systems are important for informing the future design of resilient, efficient, and sustainable transport systems. In the recent decade, there has been an emerging discourse within policy narratives that explores whether such disruptions can be a catalyst for radical sustainable transformation in transport (Marsden and Docherty, 2013, 2021; Docherty and Shaw, 2019; Williams et al., 2012; Marsden et al., 2020). This discourse critically examines the prevailing stability-oriented transport policy-making approaches, which, despite their sustainability objectives, are often conservative and fall short of the ambition needed to drive substantial change. Instead, it investigates whether societal and environmental disruptions affecting transport availability, or activities involving travel, can result in longer-term, more radical changes to travel behaviour that support sustainable outcomes – grounded in the rationale that such disruptions may present opportunities for individuals to break away from or consciously reassess unsustainable travel habits (Marsden and Docherty, 2013).

Major disruptions during the COVID-19 pandemic have recently emerged as a critical case for understanding the impacts of large-scale, prolonged disruptions on transport. These major disruptions arise mostly from two aspects. The first is the repercussions of the spread of the virus itself, especially noted primarily during the early, acute phases of the pandemic, which are characterised by the health impacts of the virus and the lack of preparedness in addressing its spread. The second aspect concerns the consequences of enforcing various stringent containment measures, such as lockdowns, restrictions on social gatherings, and social distancing policies. Insights gained from this pandemic may yield policy implications for promoting transport sustainability in the post-pandemic era and offer lessons that could be translated into managing similar disruptions in the future.

Studies suggest that major COVID-19 disruptions might have reshaped the landscape of travel demand (De Vos, 2020). In particular, a substantial body of literature has investigated contemporaneous responses in such demand amidst these disruptions, for example, during the initial COVID-19 outbreak and the phases of containment measures' enforcement and temporary easing. These studies predominantly centred on the early phase of the pandemic, typically spanning a few months post the COVID-19 outbreak or the initial lockdown in the corresponding studied areas. Evidence shows that there has been a noticeable decline in individuals' demand for public transport, attributed largely to social distancing norms and public apprehension about enclosed spaces (Gramsch et al., 2022; Carrington, 2020; Hu and Chen, 2021; Abdullah et al., 2020). In contrast, active travel demand, such as cycling and walking, has remained relatively stable or experienced an increase amidst major COVID-19 disruptions (Abdullah et al., 2020; McElroy et al., 2023; Aldred and Goodman, 2021; Costa et al., 2022), which may be driven by the necessity of maintaining physical activities and minimising direct social interaction (Woodcock et al., 2020; Zafri et al., 2021).

Yet, the understanding of how sustainable travel demand responds *in the long term* to major disruptions during the COVID-19 pandemic, along with the contextual factors shaping such long-term responses, remains limited. Here, we argue that the conceptual distinction between travel demand's contemporaneous responses and long-term responses to such disruptions should be underscored. The contemporaneous response refers to the changes in travel demand observed amidst the acute phases of COVID-19's health crisis, and the implementation phases of specific containment measures, including during their enforcement and temporary short-term easing, in comparison to demand levels in the pre-disruption phase. For example, an analysis examining changes in bike-sharing demand subsequent to the first national lockdown in England serves as an illustration within this category (see, e.g., Heydari et al. (2021) and Chibwe et al. (2021) for examples).

In contrast, the long-term response pertains to the changes in travel demand between the post-disruption and pre-disruption phases, spanning over a long-term course. This course encompasses the transition from the acute phases of the pandemic to a state of substantial relief, as well as the shift from the full spectrum of various containment enforcement periods to subsequent periods following their removal or permanent substantial relaxation. Therefore, the long-term response encapsulates the *enduring cumulative effects*, which are manifested in an extended post-disruption phase, of the major COVID-19 health crisis and various containment measures. The lack of insights into this topic hinders the comprehensive understanding of the dynamic impacts of major COVID-19 disruptions on transport sustainability. This gap also potentially undermines the applicability of policy implications derived from existing studies in promoting sustainable transport in the post-pandemic era.

This research seeks to contribute to this relatively unexplored topic by scrutinising long-term responses in bike-sharing demand to major COVID-19 disruptions and the contextual determinants of these responses. The past decade has witnessed both a rapid expansion of bike-sharing schemes (BSSs) and a surge in user demand, driven primarily by advancements in smart payment technologies and the rise of shared economy models (An et al., 2023). Meanwhile, bike-sharing is increasingly recognised as a sustainable, efficient, and adaptable transport option, offering promising solutions to various urban challenges. These include mitigating the first- and last-mile problem (Cho and Shin, 2022; Oeschger et al., 2020), alleviating traffic congestion (Wang and Zhou, 2017), improving air quality (Cao et al., 2023), and narrowing inequalities in accessibility (An et al., 2024).

Research examining the relationship between major COVID-19 disruptions and bike-sharing demand has predominantly focused on the contemporaneous effects of these disruptions. These investigations primarily utilise datasets covering the early stages of the pandemic, typically spanning from one month (Teixeira and Lopes, 2020; Hua et al., 2021; Bucsky, 2020; Hu et al., 2021) to approximately a year (Seifert et al., 2023; Heydari et al., 2021), following either the outbreak of the pandemic or the onset of initial containment measures, such as the first lockdowns. A global trend of a sharp decline in bike-sharing demand during these periods has been widely documented, as seen in countries including China (Hua et al., 2021; Shang et al., 2021), Hungary (Bucsky, 2020; Bustamante et al., 2022), the US (Hu et al., 2021), the UK (Li et al., 2021), Portugal (Albuquerque et al., 2021), and Spain (Seifert et al., 2023), although an exception was noted in Korea, where a study reported an increase in demand (Park et al., 2023). Notwithstanding, there is evidence indicating that bike-sharing demand exhibits greater resilience compared to motorised modes of transport, such as personal cars and traditional public transport in this context (Bucsky, 2020; Bustamante et al., 2022). Several studies have also suggested that, during these early stages, bike-sharing demand closely correlates with specific environmental features. An increase in leisure spaces, denser bike lanes, enhanced green infrastructure, more diverse land use, and greater availability of bikes around areas where docking stations are located are associated with higher demand, whilst areas with extensive public transport services tend to see a decrease in bike-sharing usage (Bustamante et al., 2022; Kim and Lee, 2023; Jiao et al., 2022).

Despite the decline in bike-sharing demand during the early stages of the pandemic, however, there is evidence suggesting a rebound over time, possibly attributed to the growing adoption of bike-sharing as a substitute for traditional public transport in the post-lockdown phase (Hu et al., 2021; Li et al., 2021; Wang and Noland, 2021; Teixeira et al., 2023b; Gao et al., 2023; Song et al., 2022; Bi et al., 2022). This trend highlights the potentially dynamic nature of bike-sharing demand in response to evolving disruptions associated with the pandemic, in turn underscoring the the importance of a long-term analytical perspective. For example, Hu et al. (2021) conducted a study on the variations in bike-sharing demand for commuting purposes within the City of Chicago, US, over five months following the onset of the pandemic. Their findings showed a substantial early decline in bike-sharing demand, yet such demand showed a slight rebound four months after the outbreak. Similarly, over four months following the UK's first national lockdown, Li et al. (2021) observed an immediate drop in bike-sharing demand in London, followed by a significant increase that eventually surpassed pre-lockdown levels.

Gao et al.'s (2023) recent research extends the investigation of this topic to a multi-year timeline by analysing London's bike-sharing patterns over 21 months following the first national lockdown. Despite fluctuations, a general upward trend in bike-sharing demand was observed. To date, this represents the most extended period examined in studies on this topic to the best of our knowledge. However, it is crucial to consider that the period examined in this research still overlaps with the enforcement periods of stringent containment measures, such as mandates for self-isolation, social distancing, and limitations on social gatherings, with varying intensities (see Subsection 2.1 for details). These measures may have potential influences on the adoption of other modes of transport, especially traditional public transport (Fernando et al., 2020; Kamga et al., 2021). Relying on these findings to inform long-term policymaking might therefore lead to an overestimation of the response in bike-sharing demand to COVID-19 disruptions. It remains to be inconclusive whether the observed upward trend in bike-sharing demand amidst disruptions will persistent over a longer course, particularly after the permanent removal or lasting, substantial relaxation of containment measures.

This research investigates long-term responses in bike-sharing demand to major disruptions during the COVID-19 pandemic and the contextual correlates of these responses. We use data from a public BSS in London, which consists of more than 30 million usage records spanning the 27-month pre-, 23-month amidst-, and 7-month post-disruption phases concerning the pandemic. We have three objectives: (1) to investigate the characteristics of long-term responses in bike-sharing demand to major COVID-19 disruptions; (2) to examine the extent to which such long-term responses differ from contemporaneous responses in bike-sharing demand amidst these disruptions; and (3) to explore the extent to which docking stations' contextual features (i.e., the physical design of stations as well as the demographic, socioeconomic, and built environmental characteristics of their surrounding neighbourhood) are associated with the long-term response in bike-sharing demand. Our research findings could support policies to encourage bike-sharing usage in the post-pandemic era. The findings and approaches of our research also contribute to the understanding of the long-term implications of transport-related disruptions.

2. Progression of the COVID-19 pandemic in England

The COVID-19 pandemic began its outbreak in England with the first confirmed cases reported in late January 2020. It rapidly escalated into a widespread health crisis by March 2020. The government has enacted a succession of containment measures since then, aiming at curtailing viral transmission and addressing the consequent healthcare, societal, and economic repercussions. The timeline detailing the evolution of the pandemic in England can be segmented into three major phases: the pre- (prior to March 16, 2020), amidst- (spanning March 17, 2020 to February 23, 2022), and post-disruption (beginning February 24, 2022) phases.

Throughout the 24-month *amidst-disruption* phase, England witnessed several peaks in COVID-19 infection rates and deaths. The government pursued a series of containment measures aiming to manage the pandemic. Central to these measures were the three national lockdowns that signified stringent mobility restrictions, accompanying the measures for social distancing and gathering, restricted access to amenities and public services, and mandates for self-isolation (Fig. 1). On March 16, responding to the rising health crisis, the Prime Minister addressed the nation (Prime Minister's Office, 2020), stating, '[N]ow is the time for everyone to stop non-essential contact with others and to stop all unnecessary travel.' Following this, the first lockdown began on March 23, 2020. Residents were told to stay home, venturing out only for essential purposes. The relaxation of measures began in May 2020 with a phased reopening strategy of amenities and public services, yet by September 2020, the resurgence of cases led to the introduction of new restrictions such as the 'Rule of Six' for social contact (i.e., indoor and outdoor social gatherings above six were banned) and a

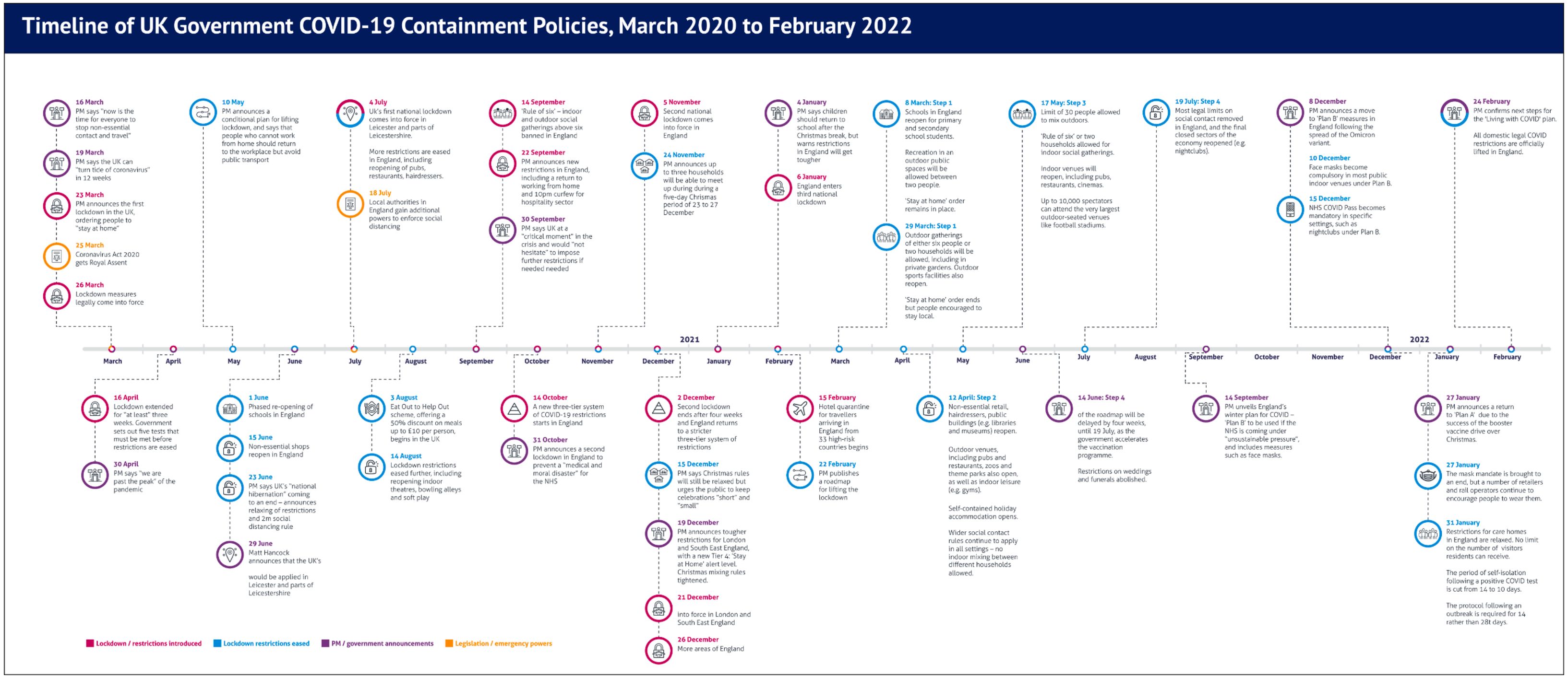

Fig. 1. Timeline of COVID-19 containment measures in England, March 2020 to February 2022. *Note*. This figure was generated based on Institute for Government (2022) (licensed under CC BY-NC), with additional information for 2022 from Santillo (2022) and Government Digital Service (2022). To maintain image quality, readers are encouraged to consult the original image for full detail. A high-resolution version is also available in the Supplementary Material (Fig. 1).

hospitality sector curfew.[1] On November 5, 2020, the second national lockdown was enforced, with restrictions similar to the first, except schools remained open and meetings of up to three households were allowed. Easements in early December 2020 introduced a tiered system of containment measures, varying regionally based on infection rates. However, the emergence of a new and more contagious variant necessitated another stringent national lockdown, the third one, which started on January 6, 2021. This lockdown included the shutdown of schools and non-essential shops, with the public required to work from home whenever possible. The implementation of these measures, alongside the vaccination program, led to a substantial decline in infections and deaths. Following the third lockdown, the government's containment measures shifted towards easing restrictions; strategic relaxation frameworks, such as 'Roadmap out of Lockdown', 'Plan A', and 'Plan B' were laid out (see Fig. 1 for details).

The commencement of the *post-disruption phase* was signified by the 'Living with COVID' policy, launched on February 24, 2022. Most domestic legal restrictions were officially lifted as the pandemic was largely managed in England,[2] a development that may have significant implications for the public's travel demand and transport preferences. Following this policy, the public was encouraged to live normally alongside the virus while maintaining a safety net of measures to prevent its spread. Notably, the policy terminated the legal mandate for self-isolation following a positive COVID-19 test. It abolished restrictions on the number of individuals allowed to congregate in private dwellings and public spaces, or at events. Work-from-home guidance was withdrawn, allowing businesses to fully reopen their workplaces. Moreover, the obligatory use of COVID passports for entry into certain events and venues was no longer legally required.

3. Research design

3.1. Data

We focus on the demand for Santander Cycles BSS in Greater London, spanning 57 months from December 27, 2017, to September 6, 2022. The BSS, also known as 'Boris Bikes', was first introduced in 2010 by Transport for London (TfL) with an initial fleet of 5000 bicycles across 315 docking stations. The scheme exclusively uses docked bicycles, which must be returned to an empty spot after use. The scheme's introduction aimed to 'offer a comprehensive package to improve the commute for those already cycling to work and encourage many thousands more to join them' (TfL, 2010). As of September 2022, the system had expanded to encompass 12,000 bicycles and 800 stations in 13 inner London boroughs.

The Stander Cycles BSS demand data presents three major strengths for analysing the long-term responses in bike-sharing demand to major COVID-19 disruptions. First, the high level of consistency in cost and availability of the BSS reduces the confounding effects of these factors in our longitudinal analysis. Notably, while there have been various offers, partnerships, and promotions throughout the years between 2018 and 2022, there were no major overhauls to the pricing structure by September 14, 2022. This date marks seven months following the extensive relaxation of COVID-19 containment measures in the UK, indicated by the implementation of the 'Living with COVID' policy. Moreover, the number of operational docking stations remained relatively stable, with 613 stations consistently operating during our study period, representing 77 % of the total active stations in September 2022. Second, TfL provides a multi-year dataset regarding Santander Cycles BSS demand, which covers the pre-, amidst-, and post-disruption phases concerning the COVID-19 pandemic in Greater London. This enables us to conduct reliable counterfactual comparisons, thereby assessing the long-term implications of major COVID-19 disruptions on bike-sharing demand. Third, the Santander Cycles BSS is effectively integrated into Greater London's transport system, playing a crucial role in residents' daily travel. In 2022, it recorded more than one million users and eleven million hires. This substantial user base and a high number of hires mitigate the influence of unexpected random temporal fluctuations of bike-sharing demand, issues often associated with less-utilised BSS, thereby enhancing the robustness of our analyses.

We used Santander Cycles BSS demand data, along with daily weather records, as inputs to time-series models for analysing responses in bike-sharing demand to major COVID-19 disruptions. The demand data were obtained via the TfL Unified API and comprise two categories: trip-level and docking station-level data. The trip-level data contain information on the origin and destination stations, start and end times, and the duration of each bike-sharing trip. The docking station-level data include the geographical coordinates and capacity details (i.e., the maximum number of bikes a station can accommodate) of each docking station. Our analysis period covered the pre- (December 27, 2017 to March 16, 2020), amidst- (March 17, 2020 to February 23, 2022), and post-disruption phases (February 24, 2022 to September 6, 2022) concerning the COVID-19 pandemic, while avoiding the confounding influence of the substantial increase in Santander Cycles users' cost from September 14, 2022 onwards and the BSS's shutdown on September 10 and 11, 2022. Our analyses were restricted to stations that operated consistently throughout the entire study period ($n = 613$, Fig. 2), which collectively accounted for 31,897,615 bike-sharing trips during this timeframe. In the pre-disruption phase, the average weekly number of outbound bike-sharing trips per station was 241.3; 60 % of stations experienced an increase in trips in the amidst-disruption phase, and this figure rose to 90 % in the post-disruption phase (Fig. 3). Daily weather records for Greater London – such as temperature, daylight hours, and precipitation – were obtained via the Visual Crossing Weather Data API. These variables were

[1] Slight regional differences existed in the relaxation and reintroduction timings of containment measures across England. The Greater London Authority, specifically, initiated the relaxation on June 1, 2021, and reimposed containment measures on September 14, 2021.

[2] Despite an increase in infection rates during the summer of 2022, likely driven by the Omicron variants, the situation remained largely under control, which was marked by low COVID-19 confirmed deaths and residents' re-engagement with pre-pandemic activities (see, e.g., Smith et al. (2022)).

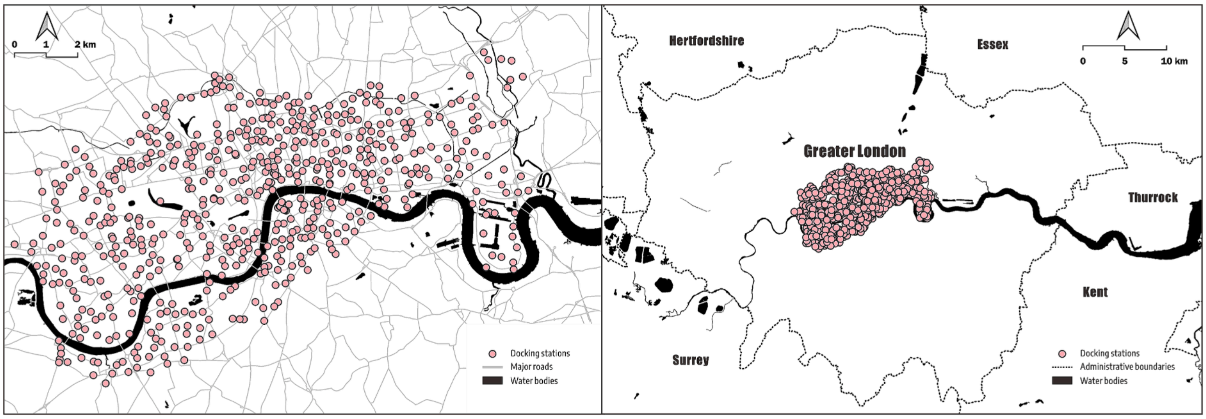

Fig. 2. The distribution of Santander Cycles docking stations.

incorporated into our time-series models to account for weather-driven fluctuations in bike-sharing demand, thereby facilitating the isolation of the impacts of major COVID-19 disruptions (see Subsection 3.3.1).

Moreover, we acquired demographic, socioeconomic, and built environment data to examine how the contextual characteristics of docking stations are associated with long-term responses in bike-sharing demand. Demographic and socioeconomic indicators, such as age structure, ethnic composition, and deprivation levels, at the Lower Layer Super Output Area (LSOA) level were obtained from the Office for National Statistics. An LSOA is a small geographic unit used for statistical and administrative purposes in the UK; each one in Greater London encompasses approximately 1800 residents and covers an area of 33 ha. Built environment data were collected from multiple sources. Land use classifications were derived from Geomni UKLand, which identifies 11 categories encompassing both man-made and natural landscapes. We obtained the street network from the Ordnance Survey MasterMap Highways Network, the most comprehensive navigable street dataset for Great Britain. Public transport accessibility measures were derived using TfL's WebCAT planning tool. Further details on the use of these data in our analyses are provided in Subsection 3.2.

3.2. Docking stations' physical design and environmental characteristics

Our measurement of each docking station's contextual features encompassed an analysis of its physical design and the environmental characteristics of its surrounding neighbourhood. The selection of the applied variables was informed by existing ecological studies concerning the correlates of bike-sharing demand (El-Assi et al., 2017; Eren and Uz, 2020; Ma et al., 2020; Zhu et al., 2022). For the docking stations' physical design, we included the count of docking points, which served as an indicator of each station's maximum capacity to accommodate bike-sharing needs, in our analysis.

We drew on Ewing and Cervero's (2010) conceptual framework on the travel demand-built environment relationship, and applied four concepts to measure the built environmental characteristics surrounding each station: density, diversity, design, and distance to transit. First, to quantify the concept of density, we employed the LSOA-level workday population density metric, which measures the density of people present in each LSOA during a typical workday, encompassing all individuals who work in the area as well as non-working residents. Recognising the intricate nature of the density concept and the diversity of quantification methodologies (Oakes et al., 2007), our analyses also took into account residential population density and workplace population density as alternatives. These metrics respectively represent the density of usual residents and the density of individuals aged 16 and over working in the area, regardless of their place of residence. Second, we employed the Shannon Entropy index, a widely used land use mix metric (An et al., 2021), to characterise the concept of diversity, based on the Geomni UKLand data set. Third, the concept of design was assessed using the LSOA-level intersection density (Lu et al., 2017; Ewing and Cervero, 2010), utilising the Ordnance Survey MasterMap Highways Network. Fourth, the concept of distance to transit, which reflects access to such services, was measured using the Public Transport Accessibility Level (PTAL) indicator assigned to each docking station's location. This indicator, developed by TfL, offers a relatively comprehensive measure of public transport accessibility by incorporating walking time and distance to nearby service points (bus stops and rail stations) via the street network, service frequency, and average waiting times during the weekday morning peak (see TfL (2015) for further details). PTAL is categorised into six levels, with higher values indicating better accessibility. One limitation is that it only accounts for walking access, excluding other modes of transport. However, as walking is arguably the most common connecting mode between docked bike-sharing and public transport, this limitation may not substantially affect the validity of our analysis.

We also included demographic and socioeconomic characteristics of the docking stations' surrounding neighbourhoods in our analyses, following the existing literature (Wang and Lindsey, 2019; Qian and Jaller, 2020; Eren and Uz, 2020). These characteristics encompassed the percentage of the White population, male-to-female ratio, percentage of working-age residents, number of households, percentage of households with at least one vehicle, and the percentage of non-deprived households at the LSOA level.

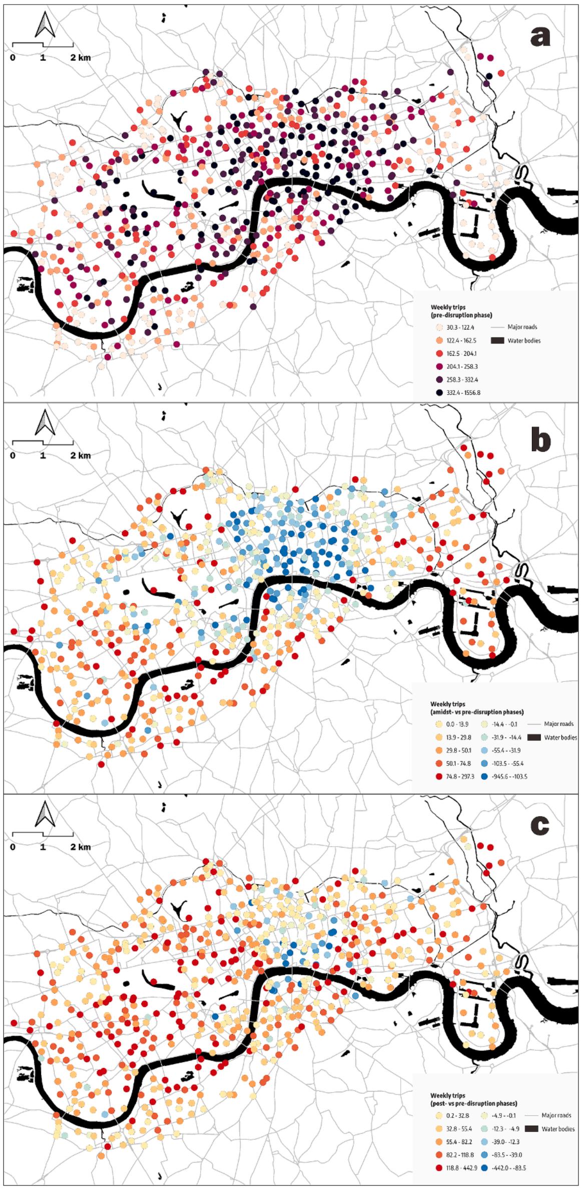

Fig. 3. The distribution of (a) weekly trip counts; (b) changes in weekly trip counts between the amidst- and pre-disruption phases; and (c) changes in weekly trip counts between the post- and pre-disruption phases, at each docking station. *Note.* The number of weekly trips is binned using the equal count method. For changes, increases and decreases are binned separately using the equal count method.

3.3. Analytical approaches

This subsection elaborates on the approaches applied to achieve our objectives: (1) assessing long-term responses in bike-sharing demand to major COVID-19 disruptions; (2) analysing discrepancies between long-term responses and contemporaneous responses in bike-sharing demand to such measures; and (3) examining the association between bike-sharing demand's long-term responses and docking stations' contextual features.

3.3.1. Measuring responses in bike-sharing demand

To fulfil our objectives (1) and (2), we applied a time-series approach – the Bayesian dynamic generalised linear model (BDGLM) – to bike-sharing demand in the pre-disruption phase, thereby constructing counterfactual scenarios for demand in the amidst- and post-disruption phases as if unaffected by major COVID-19 disruptions. On this basis, we quantify the long-term and contemporaneous responses of bike-sharing demand to such disruptions. Our rationale for adopting a time-series approach lies in its ability to capture the historical temporal dynamics of bike-sharing demand to support future projections. In Greater London, where bike-sharing demand has surged since the introduction of Santander Cycles, this approach enables a more precise attribution of the impacts of major COVID-19 disruptions.

The BDGLM presents three principal advantages in our analyses. First, it effectively separates deterministic temporal components, such as local trends and seasonal patterns of bike-sharing demand we are interested in, from stochastic components like random noise (West and Harrison, 2006). Second, the model captures the influence of covariates on the temporal evolution of the interested variable, which allows for accounting for changes in external factors that could potentially skew the understanding of temporal patterns. These two features enhance the model's reliability for counterfactual comparisons across different periods, offering a more robust interpretation than reliance on observed raw data alone. Third, in comparison with conventional linear time series models, such as the autoregressive moving average model and the exponential smoothing model, the BDGLM exhibits a heightened resistance to over-fitting and demonstrates superior capability in capturing complex temporal dependencies and interactions within the data (Kearns et al., 2019; Barber et al., 2011). A BDGLM is formulated through two main components: the observation equations and the state equations. For bike-sharing demand for a given station in week t, we specify the observation equations as follows:

$$y_t = \text{Poisson}(\lambda_t) \tag{1}$$

$$\lambda_t = e^{\left(\boldsymbol{F}_t^\top \boldsymbol{\theta}_t\right)} \tag{2}$$

where y_t represents the number of outbound trips, which is assumed to follow a Poisson distribution with the expected value λ_t. $\boldsymbol{F}_t$ denotes a design column vector of the level and slope for local trends $(1, t)$, covariates $(x_{1t}, \ldots, x_{nt})$, and Fourier terms for seasonalities $(\cos(2\pi t/s_1), \sin(2\pi t/s_1), \ldots \cos(2\pi t/s_n), \sin(2\pi t/s_n))$. We included temporal covariates, which are potentially associated with bike-sharing demand: the number of public holidays, average daily mean temperature, average daily precipitation, average daily precipitation coverage, average daily snowfall, average daily wind speed, average daily dew points, and average daily visibility in week t. We considered three types of potential seasonalities (i.e., yearly, biannually, and quarterly seasonalities for s_1, s_2, and s_3) to better capture the cyclical patterns and long-term temporal dynamics of bike-sharing demand over time. $\boldsymbol{\theta}_t$ is a state vector of time-varying parameters to be estimated (i.e., local trend and seasonal components), with the regression coefficients for covariates included but treated as static by assigning a zero evolution variance. Its evolution process is defined in the state equations:

$$\boldsymbol{\theta}_t = \boldsymbol{T}\boldsymbol{\theta}_{t-1} + \boldsymbol{\upsilon}_t,\ \boldsymbol{\upsilon}_t \sim \mathcal{N}(0, \boldsymbol{W}_t) \tag{3}$$

$$\boldsymbol{T} = diag(\boldsymbol{A}_t, \boldsymbol{I}_c, \boldsymbol{A}_s) \tag{4}$$

$$\boldsymbol{A}_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \tag{5}$$

$$\boldsymbol{A}_s = diag(\boldsymbol{G}(s_1), \boldsymbol{G}(s_2), \boldsymbol{G}(s_3)),\ \boldsymbol{G}(s) = \begin{bmatrix} cos(2\pi/s) & sin(2\pi/s) \\ -sin(2\pi/s) & cos(2\pi/s) \end{bmatrix} \tag{6}$$

where $\boldsymbol{T}$ is a transition matrix, which incorporates submatrices governing the evolution of the trend ($\boldsymbol{A}_t$), covariate ($\boldsymbol{I}_c$), and seasonality ($\boldsymbol{A}_s$) components (Eq. (4)). $\boldsymbol{I}_c$ is an identity matrix of covariates, whereas matrices $\boldsymbol{A}_t$ and $\boldsymbol{A}_s$ are specified in Eqs. (5) and (6), respectively. The evolution noise $\boldsymbol{\upsilon}_t$ in Eq. (3) is assumed to follow a multivariate normal distribution with zero mean and covariance matrix $\boldsymbol{W}_t$, which is specified with a block-diagonal structure:

$$\boldsymbol{W}_t = \text{diag}\left(\boldsymbol{W}_{t,t}, \boldsymbol{0}_c, \boldsymbol{W}_{t,s}\right) \tag{7}$$

where $\boldsymbol{W}_{t,t}$ and $\boldsymbol{W}_{t,s}$ represent the evolution variances of the trend and seasonal components, respectively, and $\boldsymbol{0}_c$ is a zero matrix corresponding to the static covariate coefficients.

We let $\boldsymbol{C}_{t-1}$ be the posterior covariance of the state vector at time $(t-1)$. Then $\boldsymbol{R}_t$ serves as its prior covariance matrix of the state vector at time t (Eq. (8)). We define $\boldsymbol{W}_{t,t}$ and $\boldsymbol{W}_{t,s}$ as scaled submatrices of the one-step forecast covariance matrix $\boldsymbol{R}_t$ (Eq. (9)), where a discount factor ρ is introduced to control the gradual integration of new trends and seasonal patterns, while preserving historical baselines. $\boldsymbol{P}_{t-1,\ t}$ and $\boldsymbol{P}_{t-1,\ s}$ denote the submatrices of $\boldsymbol{R}_t$, corresponding to the trend and seasonal components, respectively.

$$\boldsymbol{R}_t = \boldsymbol{T}\boldsymbol{C}_{t-1}\boldsymbol{T}^\top \tag{8}$$

$$\boldsymbol{W}_{t,t} = \frac{(1-\rho)}{\rho}\boldsymbol{P}_{t-1,t},\ \boldsymbol{W}_{t,s} = \frac{(1-\rho)}{\rho}\boldsymbol{P}_{t-1,s} \tag{9}$$

For our objective (1), we trained BDGLMs using pre-disruption phase bike-sharing demand data. The trained models were then used to project bike-sharing demand in the post-disruption phase, assuming a counterfactual scenario without major disruptions from the pandemic. We applied the BDGLM to each docking station separately, considering the potential heterogeneity in their bike-sharing demand over time. The models were trained through a Markov Chain Monte Carlo approach, utilising 20 separate Markov chains to ascertain convergence and generating 100,000 samples per chain to ensure the robustness of training. A copula approach was then used for the projection (Lavine et al., 2022). The projected demand, labelled as the *projected without-disruption demand*, was compared with the actual bike-sharing demand in the same phase, referred to as the *actual post-disruption demand*. Through this counterfactual comparison, the long-term responses in bike-sharing demand to major COVID-19 disruptions at the overall system level can be quantified:

$$R_s = \left(\sum_{w=1}^{m}\sum_{i=1}^{n}(D_{iw,a}) - \sum_{w=1}^{m}\sum_{i=1}^{n}(D_{iw,p})\right) / \sum_{w=1}^{m}\sum_{i=1}^{n}(D_{iw,p}) \tag{10}$$

where R_s denotes the overall system's long-term response in bike-sharing demand. $D_{iw,\ a}$ and $D_{iw,p}$ signify the actual post-disruption demand and the projected without-disruption demand for station i during week w, respectively. n and m respectively correspond to the total number of docking stations and weeks spanning the post-disruption phase. Therefore, R_s quantifies the proportionate change in bike-sharing demand at the system level, relative to a counterfactual scenario absent the major COVID-19 disruptions, in the post-disruption phase. Our approach conceptually aligns with existing studies that use counterfactual analysis to capture relative changes in travel demand for assessing the impacts of major disruptions during the pandemic (Xiao et al., 2022; Hu and Chen, 2021). Following this definition, long-term responses in bike-sharing demand at the docking station level can also be quantified, as shown in Eq. (11). For statistical inference, we applied the bias-corrected and accelerated (BCa) bootstrap method with 10,000 samples to determine the 95 % CI of these responses.

$$R_i = \left(\sum_{w=1}^{m}(D_{iw,a}) - \sum_{w=1}^{m}(D_{iw,p})\right) / \sum_{w=1}^{m}(D_{iw,p}) \tag{11}$$

For our objective (2), we quantified contemporaneous responses in bike-sharing demand amidst COVID-19 disruptions by conducting similar counterfactual analyses. These compared actual demand during the amidst-disruption phase with projected demand for the same phase. The measured contemporaneous responses quantify the proportionate change in bike-sharing demand at the system or docking station level, relative to a counterfactual scenario absent the major COVID-19 disruptions, in the amidst-disruption phase. To investigate the differences between the contemporaneous and long-term responses, we applied the BCa bootstrap method, which allowed us to statistically examine the extent of alignment or misalignment between the two. The containment measures, e.g., those affecting social gatherings and the closure of non-essential services, enforced during three national lockdowns were notably more stringent, potentially leading to a more pronounced impact on bike-sharing demand. To gain a deeper insight into the potential persistence of the effects of disruptions during the pandemic, we also scrutinised the differences between the long-term and contemporaneous responses, deliberately excluding the periods of lockdowns in the latter assessment. This allows for a more comprehensive understanding of how major COVID-19 disruptions have reshaped bike-sharing demand over different phases of the pandemic.

In our analysis of the responses in bike-sharing demand, we considered several categories of trips: (1) overall trips, encompassing all departures from the focused docking stations; (2) peak hour and off-peak hour trips, with peak hours defined as Monday to Friday (excluding public holidays) from 06:30 to 09:30 and 16:00 to 19:00, and all other times categorised as off-peak hours; and (3) trips of different durations, specifically short (less than 600 s), medium (600–1140 s), and long (over 1140 s) durations. These trip categories are exclusively limited to outbound trips, as defined in Eq. (1); thus, the aggregate of trips within each category reflects the respective overall demand for the bike-sharing system. These duration categories were set up based on trip duration tertiles in our dataset. The stratification of trip types enhances our understanding of the nuanced, long-term implications of major COVID-19 disruptions on bike-sharing demand. It should be noted that while one might anticipate the projected without-disruption demand for overall trips to precisely align with the aggregate of projected demands for subcategory trips, this may not necessarily hold true for time-series modelling. The deviation, which was observed to be marginal in our analyses, could be attributed to the inherent disparities arising from latent interactions between trip categories that are embedded in the overall demand data and implicitly absorbed by the BDGLM, as well as to the potentially distinct deterministic temporal components and uncertainties embedded in demand for each trip category. Despite this, the stratification analyses remain valuable by offering insights into the major contributors that underpin the changes in bike-sharing's overall demand amidst- and post-disruption.

We evaluated the models' performance using a training-validation approach, where bike-sharing overall demand data from week 1 to week 105 (December 27, 2017–December 31, 2019) in the pre-disruption phase served as the training set. Projection accuracy was then evaluated against the remaining pre-disruption data (week 106 to week 116; January 1, 2020–March 16, 2020), using the average mean absolute percentage error (MAPE).[3] MAPE measures the extent to which projections deviate from actual values, with lower values indicating better performance. MAPE was 15.8 % on average across stations and 7.6 % for the entire BSS, indicating acceptable projection performance (Kumar and Vanajakshi, 2015; Chang et al., 2007). For comparison, we applied the seasonal autoregressive integrated moving average with exogenous regressors (SARIMAX) model and the exponential smoothing model – two approaches widely used in studies of travel demand amidst the COVID-19 pandemic (Hong et al., 2021; Chang et al., 2024; Świderski et al., 2024; Jaber et al., 2022) – using the same training-validation strategy. Model parameters were determined via a stepwise search algorithm

[3] The BDGLM is not designed to support in-sample forecasting, which necessitates the use of untrained data to assess the model's predictive ability. In our main analyses, we used complete pre-disruption phase data for model training to conduct counterfactual comparisons. Given the prevalence of COVID-19 cases and the enactment of containment policies in the amidst-disruption phase, a viable method to evaluate the performance of our models is to separate pre-disruption phase data into two sets: one for training and one for validation. This deliberate partitioning for the model's performance assessment is aimed at preserving the consistency of the model configuration as in our main analyses, which involves using a long period for model training, whilst ensuring relatively adequate spans are available for effective performance assessment.

for the SARIMAX model, and through grid search for the exponential smoothing model. The resulting MAPE values were 20.3 % and 10.8 % for the SARIMAX model, and 22.4 % and 15.3 % for the exponential smoothing model, corresponding to station-level and system-level projection accuracy, respectively. Together, our examinations indicate that the BDGLM is suitable for demand projection for our data set.

3.3.2. Linking docking stations' contextual features with long-term responses

For objective (3), we applied the multilevel regression model to examine the extent to which the contextual features of docking stations correlated with the long-term response in bike-sharing demand to major COVID-19 disruptions. The choice of this model is justified by the inherent structure of our data, where docking stations are nested within LSOAs. This nesting creates a hierarchical data framework, which necessitates a modelling approach capable of simultaneously addressing variability at both the docking station and LSOA levels (Gelman and Hill, 2006). Such an approach is crucial for effectively isolating the impacts of specific variables from the broader, unobserved influences that are pervasive at the LSOA level. Multilevel regressions are particularly suitable for this task due to their structure, which incorporates both fixed effects to estimate the influence of observed variables and random effects to account for the variability within and across LSOAs. For our analysis, we used contextual features of docking stations outlined in Subsection 3.2 as explanatory variables; the measured station-level long-term response in overall bike-sharing demand served as the outcome variable. The potential multicollinearity amongst explanatory variables was checked using the variation inflation factor (VIF; best if <4, see Dodge (2008) for the discussions), and we found no high-level multicollinearity that could severely bias our statistical inference.

3.3.3. Sensitivity analyses

To enhance the robustness of our findings, we performed two sets of sensitivity analyses to address the potential confounding effects of two external factors during the pandemic – the presence of COVID-19 cases and the introduction of low-traffic neighbourhoods (LTNs) – on our evaluation of the responses in bike-sharing demand to major COVID-19 disruptions.

First, the summer of 2022 witnessed an increase in COVID-19 infection rates, largely attributed to the spread of the Omicron variant. Despite a high vaccination rate that kept the situation largely under control, evidenced by low COVID-related deaths and residents' re-engagement with pre-pandemic activities (see, e.g., Smith et al. (2022)), the presence of COVID-19 cases in the post-disruption phase might confound the long-term implications of COVID major disruptions on bike-sharing demand. We therefore used random forest regression, which has been widely recognised for its projection accuracy (Breiman, 2001), to calibrate the actual post-disruption demand under a hypothetical scenario absent of COVID-related deaths and hospitalisations. The model was trained using weekly demand data from the post-disruption phase, incorporating the number of COVID-related deaths and hospitalisations, temporal factors, and fixed effects of stations and week numbers as covariates. A grid search strategy was used to optimise the hyperparameters (Genuer et al., 2020). We then projected bike-sharing demand for the same phase under the assumption of no COVID-related deaths and hospitalisations. This projected 'COVID-free' demand was used to replace the actual post-disruption demand, and then compared with the projected demand without disruption, as we previously explained, to assess the long-term post-disruption responses.

Second, we addressed the confounding effects arising from the introduction of LTNs during the pandemic, which was a part of the city's Emergency Active Travel Fund aimed at reducing motorised traffic from residential streets and promoting active transport (Dudley et al., 2022). During the period from the pandemic outbreak to September 6, 2022, 30 LTNs were put into operation in inner London. Despite limited evidence, it has been suggested that LTNs might encourage individuals' active travel within their boundaries (Goodman et al., 2020). Employing random forest regressions, we calibrated actual bike-sharing demand amidst- and post-disruption, assuming no LTN introduction. LTN data, including geographic coverage and dates of implementation and removal, were sourced from ATA (2022). A docking station was considered influenced by LTNs if located within an LTN boundary or within a 400 m (i.e., 5-minute walking) buffer zone surrounding an LTN. This calibration approach mirrored that of the 'COVID-free' scenario, substituting COVID-19-related variables with a binary variable for LTN influence, to project demand in the absence of LTNs.

Table 1
The comparison between the long-term and contemporaneous responses in bike-sharing demand to major COVID-19 disruptions.

Bike-sharing demand	Long-term response	Contemporaneous response	Statistical significance of difference
Overall trips	0.273 (0.260, 0.285)	0.112 (0.107, 0.117)	$p < 0.001$
Peak-hour trips	0.090 (0.079, 0.103)	−0.203 (−0.207, −0.198)	$p < 0.001$
Off-peak-hour trips	0.261 (0.245, 0.275)	0.297 (0.292, 0.302)	$p < 0.001$
Short-duration trips	0.289 (0.277, 0.303)	−0.067 (−0.072, −0.062)	$p < 0.001$
Medium-duration trips	0.175 (0.160, 0.191)	0.031 (0.026, 0.037)	$p < 0.001$
Long-duration trips	−0.055 (−0.068, −0.041)	0.277 (0.270, 0.284)	$p < 0.001$

Note. We report the mean value and corresponding 95 % CI of responses of bike-sharing demand to major COVID-19 disruptions.
Following Eq. (10), the mean value of long-term responses was calculated based on the counterfactual comparison between projected without-disruption demand and actual post-disruption demand in the post-disruption phase, whereas that of contemporaneous responses was calculated based on the counterfactual comparison between projected without-disruption demand and actual amidst-disruption demand in the amidst-disruption phase. The 95 % CI was determined using the BCa bootstrap method.
The statistical significance of the difference between long-term and contemporaneous responses was examined using the BCa bootstrap method.

4. Results

4.1. Long-term responses

The long-term response in overall trip demand was 0.273 (95 % CI: 0.260, 0.285) (Table 1). This indicates that, over the long term, i.e., over the course of the 101-week amidst-disruption and 28-week post-disruption phases, major COVID-19 disruptions have significantly contributed to a 27 % increase in overall bike-sharing demand in the post-disruption phase, in comparison to a counterfactual scenario absent such disruptions. Divergent long-term responses were observed for different trip categories. The increase in off-peak hour demand (0.261; 95 % CI: 0.245, 0.275) was more pronounced than that in peak hour demand (0.090; 95 % CI: 0.079, 0.103). Demand for short- (0.289; 95 % CI: 0.277, 0.303) and medium-duration (0.175; 95 % CI: 0.160, 0.191) trips demonstrated positive long-term responses to the major COVID-19 disruptions, whilst long-duration trip demand exhibited a marginally negative response (−0.055; 95 % CI: −0.068, −0.041). Statistical analysis via the BCa bootstrap method confirmed significant disparities between the trip categories in the same domain at the level of $p < 0.001$, indicating that the long-term increase in bike-sharing demand due to major COVID-19 disruptions is predominantly concentrated in off-peak hours and short-duration trips.

Fig. 4 illustrates the changes in the long-term responses in bike-sharing demand over weeks in the post-disruption phase. Independent of trip category, trends of gradual decline were observed in these responses, with the response in overall demand decreasing from 0.71 to 0.31. These downward trends generally reached their lowest point between the 22nd and 25th weeks after the commencement of this phase (i.e., between July 20 and August 16, 2022). Subsequently, a rebound in demand was noted across various trip categories. Despite the trend of decline, the responses in demand for most bike-sharing trip categories remained predominantly positive over time. However, the demand for long-duration trips largely exhibited a negative response from the 16th week onwards (i.e., from June 8, 2022 onwards), persisting even during the rebound phase.

Our sensitivity analyses accounting for the confounding effects of COVID-19 cases during the post-disruption phase revealed highly consistent results (Table 1 in Supplementary Material). The measured long-term responses exhibited marginal decreases, not exceeding 0.03 across all trip categories, in a hypothetical scenario without COVID-related deaths and hospitalisations. A potential reason is that, compared to the actual situation, this COVID-free hypothetical scenario would have increased demand for traditional public transport such as metros and buses, potentially leading to a decreased demand for alternative public transport options like bike-sharing. The sensitivity analyses accounting for the confounding effects of LTN introduction yielded reductions in measured long-term responses under the assumption that no LTNs had been launched; the long-term response in overall demand dropped to 0.216 (Table 2 in Supplementary Material. These reductions are potentially attributable to the role of LTNs in facilitating bike-sharing use.

4.2. Long-term responses vs. contemporaneous responses

The contemporaneous response in overall trip demand was 0.112 (95 % CI: 0.107, 0.117) (Table 1). This indicates a contemporaneous increase of 11 % in bike-sharing demand amidst major COVID-19 disruptions, in comparison to a counterfactual scenario without such disruptions. However, this response was not uniform across all trip categories. Peak-hour trips saw a significant demand

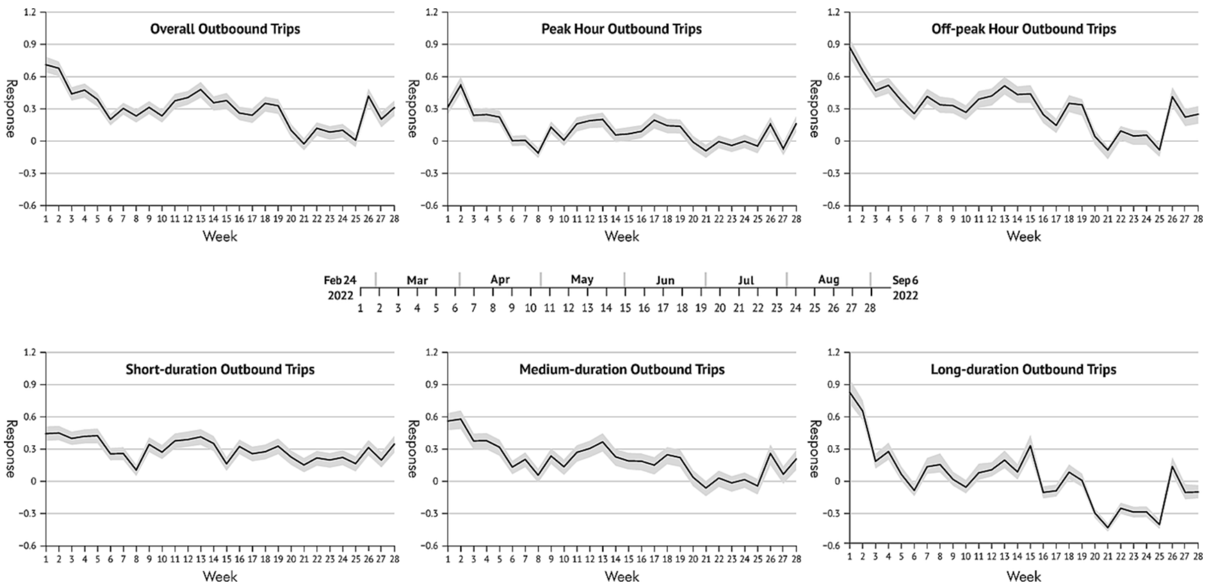

Fig. 4. Changes in long-term responses in bike-sharing demand to major COVID-19 disruptions. *Note.* This figure illustrates the long-term responses in bike-sharing demand (black lines) over a weekly timeframe. The week number corresponds to the duration in weeks within the post-disruption phase. Grey-shaded areas indicate the 95 % CI of these responses.

reduction (response: −0.203; 95 % CI: −0.207, −0.198), while off-peak-hour trip demand exhibited a substantial increase (response: 0.297; 95 % CI: 0.292, 0.302). Demand for short-duration trips decreased marginally (response: −0.067; 95 % CI: −0.072, −0.062), whereas medium-duration trips experienced a slight increase (response: 0.031; 95 % CI: 0.026, 0.037). Notably, long-duration trips showed a substantial rise in demand, with a response of 0.277 (95 % CI: 0.270, 0.284). BCa bootstrap method confirmed significant differences between the trip categories in the same domain at the level of $p < 0.001$. This indicates that the increased bike-sharing demand amidst major COVID-19 disruptions was primarily concentrated in off-peak hours and long-duration trips.

Fig. 5 illustrates the temporal evolution of the contemporaneous responses in bike-sharing demand in the amidst-disruption phase. Despite notable fluctuations, primarily during lockdown periods, upward trends were observed in the responses. This increase was similar across responses in demand for various trip categories, including peak hour, off-peak hour, short-duration, and medium-duration trips, with the response in overall trip demand increasing from −0.46 to 0.19. However, the contemporaneous response in long-duration trip demand displayed significant variability throughout this phase, diverging from the general trend of increase seen in other categories.

Through the BCa bootstrap method, we examined the discrepancies between the long-term and contemporaneous bike-sharing demand responses. For overall trip demand, the long-term responses were significantly greater than the contemporaneous response at the 0.001 significance level (Table 1). This pattern was consistent for peak-hour, short-duration, and medium-duration trip demand. In contrast, off-peak hour trip and long-duration trip demand exhibited an opposite trend, where contemporaneous responses were more pronounced. These patterns persisted when the data from the three national lockdowns during the amidst-disruption phase were excluded, although the magnitude of the differences varied due to increased contemporaneous responses (Table 2). Our sensitivity analyses, which accounted for the confounding effects of COVID-19 cases during the post-disruption phase and the introduction of LTNs after the outbreak of the pandemic (Tables 3-4 in Supplementary Material), further corroborated these findings.

4.3. *Long-term responses and docking stations' contextual features*

The multilevel regression revealed that certain contextual features of docking stations, notably built environmental characteristics, significantly correlated with the long-term responses in bike-sharing demand to major COVID-19 disruptions (Table 3). At a significance level of $p < 0.10$, stations experiencing an increased long-term response were located in areas with a more diverse land-use mix, greater intersection density, and better accessibility to public transport services. However, our analysis identified no statistical association between workday population density and the long-term response; a finding that remained consistent when the variable was replaced by residential population density or workplace population density. Conversely, a higher percentage of non-white residents at the LSOA level was negatively associated with stations' long-term response in bike-sharing demand, with its estimated standardised coefficient ranking notably amongst all explanatory variables, indicating the presence of social inequalities in how bike-sharing demand reacts to major COVID-19 disruptions. In addition to these, two variables emerged as marginally significant: the number of docks at a station was positively associated with the long-term response, whilst the percentage of LSOA-level working-age residents showed an inverse association. Our sensitivity analyses, accounting for the confounding effects of COVID-19 cases and the introduction of LTNs, in measuring the long-term response, yielded consistent results concerning the direction and significance of the coefficients.

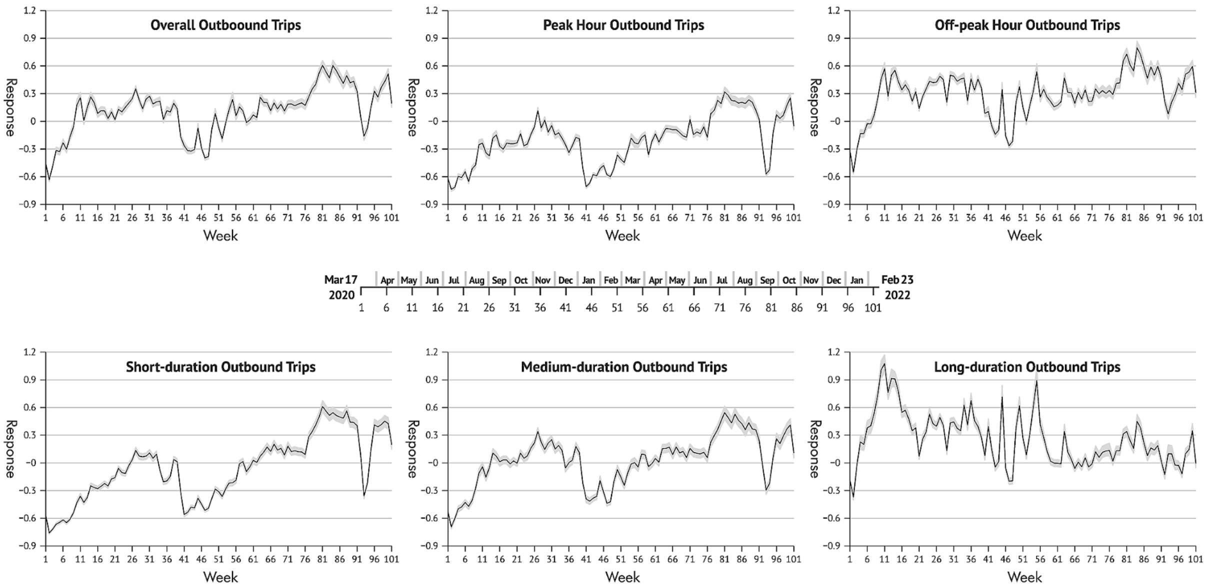

Fig. 5. Changes in contemporaneous responses in bike-sharing demand amidst major COVID-19 disruptions. *Note.* This figure illustrates the contemporaneous responses in bike-sharing demand (black lines) over a weekly timeframe. The week number corresponds to the duration in weeks within the amidst-disruption phase. Grey-shaded areas indicate the 95 % CI of these responses.

Table 2
The comparison between the long-term and contemporaneous responses (excluding lockdown periods) in bike-sharing demand.

Bike-sharing demand	Long-term response	Contemporaneous response (excluding lockdown periods)	Statistical significance of difference
Overall trips	0.273 (0.260, 0.285)	0.194 (0.189, 0.200)	$p < 0.001$
Peak-hour trips	0.090 (0.079, 0.103)	−0.116 (−0.121, −0.111)	$p < 0.001$
Off-peak-hour trips	0.261 (0.245, 0.275)	0.365 (0.359, 0.371)	$p < 0.001$
Short-duration trips	0.289 (0.277, 0.303)	0.044 (−0.038, 0.049)	$p < 0.001$
Medium-duration trips	0.175 (0.160, 0.191)	0.120 (0.113, 0.126)	$p < 0.001$
Long-duration trips	−0.055 (−0.068, −0.041)	0.281 (0.273, 0.290)	$p < 0.001$

Note. We report the mean value and corresponding 95 % CI of responses of bike-sharing demand to major COVID-19 disruptions.
Following Eq. (10), the mean value of long-term responses was calculated based on the counterfactual comparison between projected without-disruption demand and actual post-disruption demand in the post-disruption phase. The mean value of contemporaneous responses was calculated based on the counterfactual comparison between projected without-disruption demand and actual amidst-disruption demand in the amidst-disruption phase excluding periods covering the three national lockdowns. The 95 % CI was determined using the BCa bootstrap method.
The statistical significance of the difference between long-term and contemporaneous responses was examined using the BCa bootstrap method.

Table 3
The association between docking stations' contextual features and the long-term response in bike-sharing demand to major disruptions during the COVID-19 pandemic.

Variables	Coef.	Std. Err.	Significance
Intersect	0.924	1.072	0.389
Physical design			
Number of docks	0.005	0.003	0.128
Social environments of surrounding neighbourhood			
Percentage of white	1.219 **	0.411	0.003
Male-to-female ratio	−0.068	0.308	0.826
Percentage of working-age residents	−1.916	1.201	0.111
Number of household	−0.207	0.192	0.281
Percentage of households with vehicles	−0.393	0.540	0.467
Percentage of non-deprived households	−0.112	0.412	0.786
Built environments of surrounding neighbourhood			
Land area	0.002	0.001	0.090
Workday population density	−0.140	0.372	0.706
Land use mix	0.249 *	0.121	0.040
Intersection density	0.017 **	0.008	0.028
Public transport access level	0.047 †	0.026	0.073
LSOA-level variation: 0.0578			
Log-likelihood: −680.2			

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$.
Note. To ensure an accurate presentation of the estimated coefficients, the number of households and workday population density were scaled down by 100 when included in the regression.

5. Discussions

5.1. Principal findings and policy implications

This research investigates the long-term response in bike-sharing to major disruptions during the COVID-19 pandemic. Our findings reveal that these major disruptions contribute, in the long term, to an overall increase of more than 20 % in bike-sharing demand in London post-disruption, compared to a counterfactual scenario absent such disruptions. The influence of disruption-induced changes in travel habits may play an important role in shaping the observed increased bike-sharing demand post-disruption. Transport-related disruptions like the major disruptions during the pandemic, perceived as instances of changes in personal circumstances, potentially prompt individuals to either break away from or consciously reassess their travel habits (Marsden and Docherty, 2013, 2021). Social psychological studies have also highlighted the importance of experimental and adaptive behaviour in response to such changes in laying the groundwork for more established or even habitual behaviour (Jones and Sloman, 2003).

Bike-sharing usage offers various benefits amidst the major COVID-19 disruptions. It, for example, may improve perceived mental health by providing an accessible way to engage with the outdoors, thereby alleviating mental issues like social isolation and boredom during the pandemic (Teixeira et al., 2022b). In cities in which people tend to travel by public transport, BSS also supports minimising direct social interaction during travel and maintaining physical activities (Teixeira et al., 2022a). Given these advantages, an increase in bike-sharing usage during this period, particularly the period excluding stringent lockdowns, seems plausible. Our research confirms this trend, which shows an 11 % increase in bike-sharing demand amidst the major COVID-19 disruptions, in comparison with the pre-disruption level. Such amidst-disruption changes may, in turn, contribute to more established or even habitual behaviour of bike-sharing usage. This is corroborated by our findings on the difference between the contemporaneous and long-term responses, which indicates that the positive implications of major COVID-19 disruptions on bike-sharing demand might persist or even intensify after the pandemic was eased and containment measures were permanently removed.

Our analysis identified distinct variations in bike-sharing demand's long-term responses to major COVID-19 disruptions across trip categories. The increase in demand was predominantly concentrated in off-peak hours and for short-duration (<600 s) trips. This may indicate a trend towards more non-work-related, localised bike-sharing usage, which indicates bike-sharing's broader integration into daily routines for non-commuting purposes, such as shopping and errands, and as an option for short-distance travel. It would be interesting to investigate the relation between this and the changes in working practices during the pandemic, when telecommuting and hybrid work models became more prevalent (Kogus et al., 2022; Ali et al., 2023). Although commuting practices changed during the pandemic, to a large extent those changes did not involve a mode shift but rather a reduction in travel. As such, there may have been little opportunity to develop new habits of commuting by active travel. Similarly, business travel is also impacted. The need for those trips was reduced by home working and the rise in the use of videoconferencing. Moreover, we observed a substantial rise in demand for longer-duration trips during off-peak hours amidst the disruption, which may correspond to the use of bike-sharing as a recreational activity to engage with outdoor environments. Yet, this pattern did not persist post-disruption, which potentially suggests an increasingly more instrumental role of bike-sharing for short-trip needs as conditions normalised.

In the recent decade, there has been an emerging discourse within policy narratives that investigates whether disruptions can be a catalyst to radical sustainable transformation in transport (Marsden and Docherty, 2013, 2021; Docherty and Shaw, 2019; Williams et al., 2012; Marsden et al., 2020). Our findings on the long-term implications of major COVID-19 disruptions on overall bike-sharing demand shed new light on such narratives, suggesting how disruptions may function to change sustainable travel demand over the long term.

However, we should be very cautious in drawing conclusions about the relationship between these disruptions and transport sustainability. It remains unclear whether the rise in bike-sharing demand following the major COVID-19 disruptions leads to modal shifts, what the nature of these shifts entails, and whether it facilitates the use of other public transport options such as buses and metros. In scenarios where individuals switch to bike-sharing from walking, private bike usage, and the use of conventional public transport, rather than from using private cars, the increase in bike-sharing demand may not substantially contribute to sustainability in the transport sector. While no long-term evidence yet exists, it has been observed that bike-sharing was more likely to substitute public transport within intensive and congested public transport networks, and was less likely to replace private cars during the early phase of the pandemic (Teixeira et al., 2023a; Kwon and Akar, 2023). Nonetheless, it is also important to recognise that a shift away from (over-)crowded conventional public transport options to bike-sharing helps improve their attractiveness, which potentially offers an indirect way to support transport sustainability. Careful consideration of these complexities and trade-offs is essential before drawing conclusions on the long-term implications of major disruptions during the pandemic.

In three distinct ways, our findings indicate that the long-term implications of disruptions for travel demand and sustainable mobility depend on deliberate action to create conditions to facilitate active travel. To begin, our findings demonstrate that despite the overall increase in bike-sharing demand post-disruption, the magnitude of the increase flattens over time. This downward trend suggests that the benefits bike-sharing gained from the disruptions may diminish or even disappear in the future, and that such benefits may not be automatically sustained without persistent, proactive policy efforts. As previously discussed, the implications of long-term disruptions, like those during the pandemic, on travel behaviour might persist or even intensify after the disruption subsides. However, our findings suggest that even multi-year long-term disruptions may not have a strong lasting influence on travel habits over a prolonged period post-disruption. Recognising this, it is crucial to create an environment that consistently supports and benefits sustainable mobility post-disruption, thereby better leveraging the potential benefits brought by such disruptions.

Second, our research shows that the contextual characteristics of docking stations are positively associated with bike-sharing demand's long-term responses to major COVID-19 disruptions. We find that increased long-term responses tend to occur at stations located in areas with a higher land use mix, greater intersection density, and better accessibility to public transport. These built environmental features are well-acknowledged as cycling-conducive (e.g., see Heinen et al. (2010) and Fraser and Lock (2011) for reviews on this topic), and facilitators of bike-sharing usage in the early acute phase of the pandemic (Bustamante et al., 2022; Kim and Lee, 2023; Jiao et al., 2022). Our study extends these findings by demonstrating that these features may also serve as catalysts for long-term resilience and growth in bike-sharing demand in the face of COVID-19 disruptions. These contributions highlight the multifaceted practical value of investing in and adapting cycling-friendly built environments, not only to encourage bike-sharing usage in routine, everyday settings, but also to effectively respond to similar disruptions like the pandemic in the future.

Third, we found existing inequalities replicated in the long-term impacts of the disruption. The ethnic composition of docking stations' surrounding neighbourhood was closely connected with how bike-sharing demand responds to major COVID-19 disruptions in the long term. An increased level of long-term response is observed in docking stations situated in areas with a lower minority population percentage. Ethnic disparities in bike-sharing adoption have been widely documented in the existing literature prior to the pandemic. For example, in 2017, the white population disproportionately constituted 86 % of the Santander Cycles members (TfL, 2018), whereas they represented 57 % of Greater London's overall population (ONS, 2018). This pattern aligns with observations in other high-income countries (Grasso et al., 2020; Franckle et al., 2020; Dill and McNeil, 2021). Barriers to cycling and bike-sharing usage amongst ethnic minorities, such as limited access to cycling networks, potentially contribute to such disparities (Bednarowska-Michaiel, 2023; Goodman and Aldred, 2018). While our research does not determine the reasons for varying long-term responses in bike-sharing demand based on area-level ethnic composition, it contributes to the existing literature by revealing a crucial observation: the major disruptions during the pandemic have potentially aggravated the pre-existing ethnic disparities in bike-sharing adoption.

5.2. Future research avenues

This research is amongst the initial explorations into the long-term implications of COVID-19 disruptions on the demand for sustainable transport. We utilised high-quality, multi-year data, applied advanced time-series methodologies, conducted stringent statistical examinations, and performed in-depth sensitivity analyses. Our research nevertheless presents several limitations, which open up avenues for future research. First, we focus on a BSS in London, and therefore our findings may not be generalisable to other contexts. For example, in countries like China and the Netherlands, where private bikes and other private micromobility options were widely used before the pandemic, the demand for bike-sharing may not significantly increase post-COVID-19 due to the resilience of these modes during the pandemic's initial phase (Bucsky, 2020; Bustamante et al., 2022). Revisiting our research findings in other contexts with different transport cultures, pandemic conditions, and socioeconomic backgrounds is warranted.

Second, while we conducted in-depth sensitivity analyses to ensure the robustness of our results, we acknowledge that we were not able to fully account for the influence of factors, such as policies, built environmental features, and demographic composition, that changed during the pandemic. This limitation may affect the accuracy of our estimated responses in bike-sharing demand, as changes in these factors may have contributed to variation in bike-sharing demand. Future studies would benefit from incorporating a broader range of relevant factors to better capture the impacts of pandemic-related disruptions.

Third, we did not take into account trip purposes in our analyses, although the trip duration and departure time, which were included in our analyses, are closely related to trip purposes and have served as proxies in the existing literature (Hu et al., 2021). However, the response in bike-sharing demand to COVID-19 disruptions may differ depending on trip purpose. For example, Teixeira et al. (2022a) observed a decrease in bike-sharing for commuting but a slight increase in shopping and leisure in the nine months following the pandemic outbreak. While acquiring data with a large sample size (i.e., a large number of trips and stations), long coverage periods, and detailed trip-level information is highly challenging, recent advancements in statistical methodologies have demonstrated the potential to deduce trip-level information from large-scale bike-sharing datasets using survey data. This offers a feasible method to analyse long-term variations in bike-sharing demand across trip purposes. For example, through the use of a rule-based algorithm, Wan and Bendavid (2024) effectively matched trip purposes for shared e-scooter usage data in London with the National Travel Survey based on shared variables like day of week, trip start time, trip distance, and trip duration.

Fourth, our research is limited to the examination of demand for bike-sharing, without considering the demand for other modes of transport, such as shared e-scooters, buses, and metros, and how these modes interact with bike-sharing. Future studies that incorporate analyses on demand for other modes of transport could offer more comprehensive insights into the long-term implications of COVID-19 disruptions on transport sustainability.

Finally, our research provides evidence on how sustainable travel can result from disruption (if coupled with deliberate, persistent action to support sustainable travel). This understanding of how travel demand can change might have the potential to inform the design of policy measures encouraging behavioural change without a destructive disruption. Yet any such potential needs to be the subject of further investigation. Moreover, it is also a possibility that disruptions may also prompt increases in less sustainable travel, such as flights or private vehicle use. Attention to the role of disruption in changing travel demand should consider such risks.

6. Conclusion

This research investigates long-term responses in bike-sharing demand to major disruptions during the COVID-19 pandemic, and the contextual correlates of these responses. We find that major disruptions during the pandemic contribute, in the long term, to a more than 20 % rise in bike-sharing demand in the post-disruption phase, compared to a counterfactual scenario absent such disruptions. The increase in off-peak hour demand is greater than in peak hour demand. Demand for short- and medium-duration trips increases, whilst that for long-duration trips decreases slightly. However, despite the overall increase in demand post-disruption, the magnitude of the increase flattens over time. Moreover, bike-sharing demand's long-term responses surpass its contemporaneous responses. Finally, stations in areas with a more diverse land-use mix, higher intersection density, better access to public transport, and a lower percentage of minority population, show a larger long-term response in demand. We suggest that prolonged disruptions like those during the pandemic may have functioned as catalysts for the uptake of sustainable transport, such as bike-sharing. Yet, our evidence of a diminishing long-term response over time underscores a need for persistent, proactive actions to support sustainable transport after disruptions subside, if the positive response is to be sustained.

CRediT authorship contribution statement

Zihao An: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Caroline Mullen:** Conceptualization, Writing – original draft, Writing – review & editing. **Eva Heinen:** Conceptualization, Writing – original draft, Writing – review & editing.

Acknowledgements

This article forms part of work for the project COmpeting and COmplementary MObility solutions in urban contexts – CoCoMo funded by the Economic and Social Research Council (UK) (ES/W000547/1), and co-funded by JPI-Urban Europe. Our thanks go to the two anonymous reviewers for their valuable feedback, which has greatly improved the quality of this article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2025.104603.

References

Abdullah, M., Dias, C., Muley, D., Shahin, Md., 2020. Exploring the impacts of COVID-19 on travel behavior and mode preferences. Transp. Res. Interdiscip. Perspect. 8, 100255. https://doi.org/10.1016/j.trip.2020.100255.

Albuquerque, V., Andrade, F., Ferreira, J., Dias, M., Bacao, F., 2021. Bike-sharing mobility patterns: a data-driven analysis for the city of Lisbon. EAI Endorsed Trans. Smart Cities 5 (16).

Aldred, R., Goodman, A., 2021. The impact of low traffic neighbourhoods on active travel, car use, and perceptions of local environment during the COVID-19 Pandemic. Findings.

Ali, V., Corfe, S., Norman, A., Wilson, J., 2023. Hybrid work commission 2023. Public First accessed 10/02/2024.

An, Z., Heinen, E., Watling, D., 2021. The level and determinants of multimodal travel behavior: does trip purpose make a difference? Int. J. Sustain. Transp. 1–15.

An, Z., Mullen, C., Guan, X., Ettema, D., Heinen, E., 2024. Shared micromobility, perceived accessibility, and social capital. Transportation. https://doi.org/10.1007/s11116-024-10521-5.

An, Z., Mullen, C., Zhao, C., Heinen, E., 2023. Stereotypes and the public acceptability of shared micromobility. Travel Behav. Soc. 33, 100643. https://doi.org/10.1016/j.tbs.2023.100643.

ATA, 2022. "London LTN dataset." accessed 02/02/2024. https://blog.westminster.ac.uk/ata/projects/london-ltn-dataset/.

Barber, D., Taylan Cemgil, A., Chiappa, S., 2011. Bayesian Time Series Models. Cambridge University Press.

Bednarowska-Michaiel, Z., 2023. Ethnic inequalities in cycling to work in London: mobility injustice and regional approach. Reg. Stud. Reg. Sci. 10 (1), 475–488. https://doi.org/10.1080/21681376.2023.2186802.

Bi, H., Ye, Z., Zhang, Y., Zhu, H.e., 2022. A long-term perspective on the COVID-19: the bike sharing system resilience under the epidemic environment. J. Transp. Health 26, 101460. https://doi.org/10.1016/j.jth.2022.101460.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.

Bucsky, P., 2020. Modal share changes due to COVID-19: the case of Budapest. Transp. Res. Interdiscip. Perspect. 8, 100141. https://doi.org/10.1016/j.trip.2020.100141.

Bustamante, X., Federo, R., Fernández-i-Marin, X., 2022. Riding the wave: predicting the use of the bike-sharing system in Barcelona before and during COVID-19. Sustain. Cities Soc. 83, 103929. https://doi.org/10.1016/j.scs.2022.103929.

Cao, G., Zhou, L.-A., Liu, C., Zhou, J., 2023. The effects of the entries by bike-sharing platforms on urban air quality. China Econ. Quart. Int. 3 (3), 213–224. https://doi.org/10.1016/j.ceqi.2023.09.003.

Carrington, D., 2020. UK road travel falls to 1955 levels as Covid-19 lockdown takes hold. Guardian 3 (3), 2020.

Chang, A.Y.J., Wang, X., Sharafi, M., Miranda-Moreno, L., Sun, L., 2024. Headwind or tailwind? The evolution of bike-sharing and ride-hailing demand during the COVID-19 pandemic. J. Transp. Geogr. 118, 103944.

Chang, Y.F., Lin, C.J., Chyan, J.M., Chen, I.M., Chang, J.E., 2007. Multiple regression models for the lower heating value of municipal solid waste in Taiwan. J. Environ. Manage. 85 (4), 891–899. https://doi.org/10.1016/j.jenvman.2006.10.025.

Chibwe, J., Heydari, S., Imani, A.F., Scurtu, A., 2021. An exploratory analysis of the trend in the demand for the London bike-sharing system: from London Olympics to Covid-19 pandemic. Sustain. Cities Soc. 69, 102871. https://doi.org/10.1016/j.scs.2021.102871.

Cho, S.-H., Shin, D.H., 2022. Estimation of route choice behaviors of bike-sharing users as first-and last-mile trips for introduction of mobility-as-a-service (MaaS). KSCE J. Civ. Eng. 26 (7), 3102–3113.

Costa, M., Félix, R., Marques, M., Moura, F., 2022. Impact of COVID-19 lockdown on the behavior change of cyclists in Lisbon, using multinomial logit regression analysis. Transp. Res. Interdiscip. Perspect. 14, 100609. https://doi.org/10.1016/j.trip.2022.100609.

De Vos, J., 2020. The effect of COVID-19 and subsequent social distancing on travel behavior. Transp. Res. Interdiscip. Perspect. 5, 100121.

Dill, J., McNeil, N., 2021. re shared vehicles shared by all? A review of equity and vehicle sharing. J. Plan. Lit 36 (1), 5–30. https://doi.org/10.1177/0885412220966732.

Docherty, I., Shaw, J., 2019. Transport Matters. Policy Press, Bristol, UK.

Dodge, Y., 2008. The Concise Encyclopedia of Statistics. Springer Science & Business Media.

Dudley, G., Schwanen, T., Banister, D., 2022. Low traffic neighbourhoods and the paradox of the active travel agenda. accessed 13/03/2024 Polit. Q. https://politicalquarterly.org.uk/blog/low-traffic-neighbourhoods-and-the-paradox-of-the-active-travel-agenda/.

El-Assi, W., Mahmoud, M.S., Habib, K.N., 2017. Effects of built environment and weather on bike sharing demand: a station level analysis of commercial bike sharing in Toronto. Transportation 44, 589–613.

Eren, E., Uz, V.E., 2020. A review on bike-sharing: the factors affecting bike-sharing demand. Sustain. Cities Soc. 54, 101882.

Ewing, R., Cervero, R., 2010. Travel and the built environment: a meta-analysis. J. Am. Plann. Assoc. 76 (3), 265–294.

Fernando, R., Wang, H., Zhang, Y., Prakash, M., Debnath, A., 2020. The effects of travel containment measures within COVID-19.

Franckle, R.L., Dunn, C.G., Vercammen, K.A., Dai, J., Soto, M.J., Bleich, S.N., 2020. Facilitators and barriers to bikeshare use among users and non-users in a socioeconomically diverse urban population. Prev. Med. Rep. 20, 101185. https://doi.org/10.1016/j.pmedr.2020.101185.

Fraser, S.D.S., Lock, K., 2011. Cycling for transport and public health: a systematic review of the effect of the environment on cycling. Eur. J. Public Health 21 (6), 738–743.

Gao, X., Chen, H., Haworth, J., 2023. A spatiotemporal analysis of the impact of lockdown and coronavirus on London's bicycle hire scheme: from response to recovery to a new normal. Geo-Spatial Inf. Sci. (21), 1.

Gelman, A., Hill, J., 2006. Data Analysis using Regression and Multilevel/Hierarchical Models. Cambridge University Press.

Genuer, R., Poggi, J.-M., Genuer, R., Poggi, J.-M., 2020. Random Forests. Springer.

Goodman, A., Aldred, R., 2018. Inequalities in utility and leisure cycling in England, and variation by local cycling prevalence. Transport. Res. F: Traffic Psychol. Behav. 56, 381–391.

Goodman, A., Urban, S., Aldred, R., 2020. The impact of low traffic neighbourhoods and other active travel interventions on vehicle ownership: findings from the outer London mini-holland programme. Findings.

Government Digital Service, 2022. "2 Years of COVID-19 on GOV.UK." accessed 08/10/2022. https://gds.blog.gov.uk/2022/07/25/2-years-of-covid-19-on-gov-uk/.

Gramsch, B., Angelo Guevara, C., Munizaga, M., Schwartz, D., Tirachini, A., 2022. The effect of dynamic lockdowns on public transport demand in times of COVID-19: evidence from smartcard data. Transp. Policy 126, 136–150. https://doi.org/10.1016/j.tranpol.2022.06.012.

Heinen, E., van Wee, B., Maat, K., 2010. Commuting by bicycle: an overview of the literature. Transp. Rev. 30 (1), 59–96. https://doi.org/10.1080/01441640903187001.

Heydari, S., Konstantinoudis, G., Behsoodi, A.W., 2021. Effect of the COVID-19 pandemic on bike-sharing demand and hire time: evidence from Santander Cycles in London. PLoS One 16 (12), e0260969.
Hong, J., Han, E., Choi, C., Lee, M., Park, D., 2021. Estimation of shared bicycle demand using the SARIMAX Model: focusing on the COVID-19 impact of Seoul. J. Korea Inst. Intell. Transp. Syst. 20 (1), 10–21.
Hu, S., Chen, P., 2021. Who left riding transit? Examining socioeconomic disparities in the impact of COVID-19 on ridership. Transp. Res. Part D: Transp. Environ. 90, 102654.
Hu, S., Xiong, C., Liu, Z., Zhang, L., 2021. Examining spatiotemporal changing patterns of bike-sharing usage during COVID-19 pandemic. J. Transp. Geogr. 91, 102997. https://doi.org/10.1016/j.jtrangeo.2021.102997.
Hua, M., Chen, X., Cheng, L., Chen, J., 2021. Should bike-sharing continue operating during the COVID-19 pandemic? Empirical findings from Nanjing, China. J. Transp. Health 23, 101264. https://doi.org/10.1016/j.jth.2021.101264.
Grasso, H., Susan, P.B., Chavis, C., 2020. Bike share equity for underrepresented groups: analyzing barriers to system usage in Baltimore Maryland. Sustainability 12 (18), 7600.
Institute for Government. 2022. "Timeline of UK government coronavirus lockdowns and restrictions." accessed 08/10/2022. https://www.instituteforgovernment.org.uk/data-visualisation/timeline-coronavirus-lockdowns.
Jaber, A., Csonka, B., Juhász, J., 2022. Long term time series prediction of bike sharing trips: A cast study of Budapest city.
Jiao, J., Lee, H.K., Choi, S.J., 2022. Impacts of COVID-19 on bike-sharing usages in Seoul, South Korea. Cities 130, 103849.
Jones, P., Sloman, L, 2003. Encouraging behavioural change through marketing and management: what can be achieved.
Kamga, C., Tchamna, R., Vicuna, P., Mudigonda, S., Moghimi, B., 2021. An estimation of the effects of social distancing measures on transit vehicle capacity and operations. Transp. Res. Interdiscip. Perspect. 10, 100398.
Kearns, B., Stevenson, M.D., Triantafyllopoulos, K., Manca, A., 2019. Generalized linear models for flexible parametric modeling of the hazard function. Med. Decis. Making 39 (7), 867–878.
Kim, J., Lee, S., 2023. Determining factors affecting public bike ridership and its spatial change before and after COVID-19. Travel Behav. Soc. 31, 24–36. https://doi.org/10.1016/j.tbs.2022.11.002.
Kogus, A., Foltýnová, H.B., Gal-Tzur, A., Shiftan, Y., Vejchodská, E., Shiftan, Y., 2022. Will COVID-19 accelerate telecommuting? A cross-country evaluation for Israel and Czechia. Transp. Res. A Policy Pract. 164, 291–309. https://doi.org/10.1016/j.tra.2022.08.011.
Kumar, S.V., Vanajakshi, L., 2015. Short-term traffic flow prediction using seasonal ARIMA model with limited input data. Eur. Transp. Res. Rev. 7 (3), 1–9.
Kwon, K., Akar, G., 2023. What determines modal substitution between bike-sharing and public transit? Evidence from Columbus, Ohio during the COVID-19 pandemic. Int. J. Sustain. Transp. 17 (10), 1087–1096. https://doi.org/10.1080/15568318.2023.2168576.
Lavine, I., Cron, A., West, M., 2022. Bayesian computation in dynamic latent factor models. J. Comput. Graph. Stat. 31 (3), 651–665.
Li, H., Zhang, Y., Zhu, M., Ren, G., 2021. Impacts of COVID-19 on the usage of public bicycle share in London. Transp. Res. A Policy Pract. 150, 140–155. https://doi.org/10.1016/j.tra.2021.06.010.
Lu, Y.i., Xiao, Y., Ye, Yu., 2017. Urban density, diversity and design: is more always better for walking? A study from Hong Kong. Prev. Med. 103, S99–S103. https://doi.org/10.1016/j.ypmed.2016.08.042.
Ma, X., Ji, Y., Yuan, Y., Van Oort, N., Jin, Y., Hoogendoorn, S., 2020. A comparison in travel patterns and determinants of user demand between docked and dockless bike-sharing systems using multi-sourced data. Transp. Res. A Policy Pract. 139, 148–173.
Marsden, G., Anable, J., Tim, C., Iain, D., James, F., Lesley, M., Helen, R., Jeremy, S., 2020. Studying disruptive events: Innovations in behaviour, opportunities for lower carbon transport policy? Transp. Policy 94, 89–101. https://doi.org/10.1016/j.tranpol.2020.04.008.
Marsden, G., Docherty, I., 2013. Insights on disruptions as opportunities for transport policy change. Transp. Res. A Policy Pract. 51, 46–55. https://doi.org/10.1016/j.tra.2013.03.004.
Marsden, G., Docherty, I., 2021. Mega-disruptions and policy change: Lessons from the mobility sector in response to the Covid-19 pandemic in the UK. Transp. Policy 110, 86–97. https://doi.org/10.1016/j.tranpol.2021.05.015.
McElroy, S., Fitch, D.T., Circella, G., 2023. Changes in active travel during the COVID-19 pandemic. In: Loukaitou-Sideris, A., Bayen, A.M., Circella, G., Jayakrishnan, R. (Eds.), Pandemic in the Metropolis: Transportation Impacts and Recovery. Springer International Publishing, Cham, pp. 179–197.
Oakes, J.M., Forsyth, A., Schmitz, K.H., 2007. The effects of neighborhood density and street connectivity on walking behavior: the Twin Cities walking study. Epidemiologic Perspectives & Innovations 4 (1), 16.
Oeschger, G., Carroll, P., Caulfield, B., 2020. Micromobility and public transport integration: the current state of knowledge. Transp. Res. Part D: Transp. Environ. 89, 102628.
ONS, 2018. Population denominators by ethnic group, regions and countries: England and Wales, 2011 to 2018. accessed 02/02/2024.
Park, J., Namkung, O.S., Ko, J., 2023. Changes in public bike usage after the COVID-19 outbreak: a survey of Seoul public bike sharing users. Sustain. Cities Soc. 96, 104716. https://doi.org/10.1016/j.scs.2023.104716.
Prime Minister's Office, 2020. Prime Minister's statement on coronavirus (COVID-19): 16 March 2020. accessed 09/11/2023.
Qian, X., Jaller, M., 2020. Bikesharing, equity, and disadvantaged communities: a case study in Chicago. Transp. Res. A Policy Pract. 140, 354–371. https://doi.org/10.1016/j.tra.2020.07.004.
Santillo, E., 2022. Timeline of Covid-19 restrictions in England – two years of lockdowns, tiers and self-isolation." WalesOnline, accessed 08/10/2023. https://www.walesonline.co.uk/news/uk-news/timeline-covid-19-restrictions-england-23185495.
Seifert, R., Pellicer-Chenoll, M., Antón-González, L., Pans, M., Devís-Devís, J., González, L.-M., 2023. Who changed and who maintained their urban bike-sharing mobility after the COVID-19 outbreak? A within-subjects study. Cities 137, 104343. https://doi.org/10.1016/j.cities.2023.104343.
Shang, W.-L., Chen, J., Bi, H., Sui, Y.i., Chen, Y., Haitao, Yu., 2021. Impacts of COVID-19 pandemic on user behaviors and environmental benefits of bike sharing: a big-data analysis. Appl. Energy 285, 116429. https://doi.org/10.1016/j.apenergy.2020.116429.
Smith, L.E., Potts, H.W.W., Amlôt, R., Fear, N.T., Michie, S., James Rubin, G., 2022. How has the emergence of the Omicron SARS-CoV-2 variant of concern influenced worry, perceived risk and behaviour in the UK? A series of cross-sectional surveys. BMJ Open 12 (8), e061203.
Song, J., Zhang, L., Qin, Z., Ramli, M.A., 2022. Spatiotemporal evolving patterns of bike-share mobility networks and their associations with land-use conditions before and after the COVID-19 outbreak. Physica A 592, 126819. https://doi.org/10.1016/j.physa.2021.126819.
Świderski, A., Sobczuk, S., Borucka, A., 2024. Analysis of changes in transport processes in Warsaw public transport in the face of disruptions in 2019-2022. Zeszyty Naukowe Transport/Politechnika Śląska.
Teixeira, J.F., Lopes, M., 2020. The link between bike sharing and subway use during the COVID-19 pandemic: the case-study of New York's Citi Bike. Transp. Res. Interdiscip. Perspect. 6, 100166. https://doi.org/10.1016/j.trip.2020.100166.
Teixeira, J.F., Silva, C., Moura e Sá, F., 2022a. The role of bike sharing during the coronavirus pandemic: an analysis of the mobility patterns and perceptions of Lisbon's GIRA users. Transp. Res. A Policy Pract. 159, 17–34.
Teixeira, J.F., Silva, C., Moura e Sá, F., 2022b. The strengths and weaknesses of bike sharing as an alternative mode during disruptive public health crisis: a qualitative analysis on the users' motivations during COVID-19. Transp. Policy 129, 24–37.
Teixeira, J.F., Silva, C., Moura e Sá, F., 2023a. Factors influencing modal shift to bike sharing: evidence from a travel survey conducted during COVID-19. J. Transp. Geogr. 111, 103651. https://doi.org/10.1016/j.jtrangeo.2023.103651.
Teixeira, J.F., Silva, C., Moura e Sá, F., 2023b. Potential of bike sharing during disruptive public health crises: a review of COVID-19 Impacts. Transp. Res. Rec. 03611981231160537.
TfL, 2010. Mayor launches London's first two Barclays Cycle Superhighway routes. https://tfl.gov.uk/info-for/media/press-releases/2010/july/mayor-launches-londons-first-two-barclays-cycle-superhighway-routes.
TfL, 2015. Assessing transport connectivity in London. accessed 25/03/2025. https://content.tfl.gov.uk/connectivity-assessment-guide.pdf#page=56.09.
TfL, 2018. Santander Cycles Customer Satisfaction and Usage Survey: Members Only: Wave 13 (Quarter 2 2017/18).

Wan, L., Bendavid, I., 2024. Inferring trip purposes and mode substitution effect of rental e-scooters in London. Transp. Res. Part D: Transp. Environ. 126, 104034. https://doi.org/10.1016/j.trd.2023.104034.

Wang, H., Noland, R.B., 2021. Bikeshare and subway ridership changes during the COVID-19 pandemic in New York City. Transp. Policy 106, 262–270. https://doi.org/10.1016/j.tranpol.2021.04.004.

Wang, J., Lindsey, G., 2019. Neighborhood socio-demographic characteristics and bike share member patterns of use. J. Transp. Geogr. 79, 102475. https://doi.org/10.1016/j.jtrangeo.2019.102475.

Wang, M., Zhou, X., 2017. Bike-sharing systems and congestion: evidence from US cities. J. Transp. Geogr. 65, 147–154. https://doi.org/10.1016/j.jtrangeo.2017.10.022.

West, M., Harrison, J., 2006. Bayesian Forecasting and Dynamic Models, Springer Series in Statistics. Springer, New York.

Williams, D., Chatterton, T., Parkhurst, G., 2012. Using disruption as an opportunity to change travel practices.

Woodcock, J., Wright, J., Whitelegg, J., Watson, P., Walters, H., Walker, I., Uttley, J., Tulley, I., Talbot, J., Tait, C., 2020. Researchers call on government to enable safe walking and cycling during the COVID-19 pandemic an open letter.

Xiao, W., Wei, Y.D., Yangyi, Wu., 2022. Neighborhood, built environment and resilience in transportation during the COVID-19 pandemic. Transp. Res. Part D: Transp. Environ. 110, 103428. https://doi.org/10.1016/j.trd.2022.103428.

Zafri, N.M., Khan, A., Jamal, S., Alam, B.M., 2021. Impacts of the COVID-19 pandemic on active travel mode choice in Bangladesh: a study from the perspective of sustainability and new normal situation. Schol. J. 13 (12), 6975.

Zhu, L., Ali, M., Macioszek, E., Aghaabbasi, M., Jan, A., 2022. Approaching sustainable bike-sharing development: a systematic review of the influence of built environment features on bike-sharing ridership. Sustainability 14 (10), 5795.