

Vivid London: Assessing the resilience of urban vibrancy during the COVID-19 pandemic using social media data

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ABSTRACT

Since COVID-19, the focus on urban resilience has intensified, particularly on cities' ability to adapt and recover while maintaining essential functions and liveability; however, few studies have examined the resilience of urban vibrancy during such health crises. This study investigates urban vibrancy resilience in Inner London during the COVID-19 pandemic using multi-sourced social media data (geo-tagged Twitter and Flickr). We propose an analytical framework based on space-time permutation scan statistics (STPSS) to identify spatiotemporal urban areas of interest (ST-AOIs), examining their spatial, temporal, and contextual characteristics. Our findings show that central neighbourhoods with transport hubs, educational and healthcare facilities, eateries, and financial centres exhibit greater resilience. These areas adapt by shifting active periods in response to disruptions. Additionally, we assess the varying resilience capacities of different types of points of interest. This research provides actionable insights for urban planners and policymakers by demonstrating how identifying characteristics of robust urban vibrancy can contribute to the resilience of cities and communities, particularly under normal conditions after COVID-19. The findings offer concrete strategies for integrating social media data into urban planning processes, enabling more responsive and adaptive governance that meets the dynamic needs of urban populations.

1. Introduction

Urban areas are dynamic and intricate systems that function as hubs of social, economic, and cultural endeavours (Y. Liu et al., 2023). Urban vibrancy is associated with the liveliness, diversity, and allure that distinguish thriving urban locales (Jacobs, 1961). It encompasses an abundance of public engagement, bustling streets, diverse land uses, and vibrant and animated spaces that contribute to a vibrant urban atmosphere (Yue et al., 2017). However, cities encounter numerous challenges, including swift urbanisation, economic fluctuations, social inequality, environmental changes, and, more recently, unexpected disruptions such as the COVID-19 pandemic. In response to these challenges, the concepts of sustainability and resilience have gained significant attention in urban studies and planning (Afrin, Chowdhury, & Rahman, 2021; Amirzadeh, Sobhaninia, & Sharifi, 2022; Meerow,

Newell, & Stults, 2016; J. Zhang & Wang, 2023).

Sustainable urban development inherently requires resilient urban systems capable of enduring, adapting and rebounding from various disturbances and stresses while upholding their fundamental functions and liveability (Amirzadeh et al., 2022; Meerow et al., 2016). An integrated sustainability model for resilient cities, featuring domains such as energy, environment, social governance, and pandemic preparedness, which are crucial for fostering both sustainability and resilience (Abu-Rayash & Dincer, 2023). The resilience of urban vibrancy involves the adaptive capability of urban areas to sustain their dynamic and vibrant essence when confronted with disruptions (Amirzadeh et al., 2022). The integration of sustainability with resilience is crucial for addressing the challenges posed by the COVID-19 pandemic. Following the outbreak of the COVID-19 pandemic, a sequence of investigations has evaluated the degree of resilience from the perspective of public

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health, economic endeavours, urban services, infrastructure and social policies (Chu, Cheng, & Song, 2021; X. Hu, Li, & Dong, 2022; Shi, Liao, Li, & Su, 2022). Yet, there exists a scarcity of studies examining the urban vibrancy resilience in the context of such health crises, which have impacted various facets of urban vibrancy such as human mobility, economic activities, social and cultural connections, and tourism (Abbas, Mubeen, Iorember, Raza, & Mamirkulova, 2021; Ghosh, Nundy, Ghosh, & Mallick, 2020). Additionally, these studies typically have relied on the conventional and static socio-economic datasets or tailored surveys, which may encounter difficulties in capturing the nuance of fast-changing urban dynamics at fine spatial or temporal scales to assess the adaptive capacity of urban spaces.

Recent studies (T. Cheng et al., 2022; Huang et al., 2022; Niu & Zhang, 2023; Ntounis, Parker, Skinner, Steadman, & Warnaby, 2022) have demonstrated the profound impacts of the COVID-19 pandemic on everyday activities and travel patterns worldwide, including small enterprises and public transport systems. Various studies have examined these alterations to comprehend their implications for urban vibrancy. For example, there has been a transition from using public transport to using private vehicles, as well as an increase in the use of non-motorized modes of travel such as walking and cycling, and more localised movements within neighbourhoods (de Haas, Faber, & Hamersma, 2020; Gao, Rao, Kang, Liang, & Kruse, 2020). Remote work has become more common, resulting in shorter daily commutes and a shift in economic activity in commercial regions (Bick, Blandin, & Mertens, 2023). The drop in visitor numbers in parks, restaurants, cultural institutions, retail businesses, and entertainment sectors has a substantial impact on urban vibrancy (Hamidi & Zandiataashbar, 2021; Nicola et al., 2020). Although these studies emphasise significant changes in daily activities and travel behaviour, there is an absence of detailed and granular analysis that examines the extent to which these changes vary across various urban areas and over time.

During the COVID-19 pandemic, social media platforms such as Twitter (now known as X), Weibo, and Flickr have emerged as essential tools for disseminating information and facilitating communication. These platforms have enabled individuals to express their thoughts and experiences widely. The extensive data provided by social media, including geolocation, time, semantics, images, and hashtags, offers valuable opportunities for investigating the pandemic. Researchers have analysed social media semantics to understand public attitudes, sentiments, and reactions towards governmental measures and campaigns (Ainley, Witwicki, Tallett, & Graham, 2021; T. Cheng, Han, & Liu, 2023; Fazel, Zhang, Javid, Brikell, & Chang, 2021; J. Wu, Wang, He, Huang, & Dong, 2021). They have also examined how COVID-19 has influenced individuals' travel, work, and recreational activities, using location and activity data extracted from Twitter (Golder et al., 2022). Additionally, some studies have investigated the pandemic's impact on place visitation and tourism destination, such as changes in the use of urban green spaces and restaurants during the pandemic's onset (Cui, Malleson, Houlden, & Comber, 2022; S. Wang, Huang, She, & Li, 2023) and tourism destination hotspots (Taecharungroj & Mathayomchan, 2021). These studies typically rely on a single social media platform to understand people's behaviours during the pandemic, which includes only a subset of social media users and may not provide a comprehensive representation. More importantly, there is a notable lack of studies focusing on the resilience and adaptability of urban vibrancy during the COVID-19 pandemic, despite the increasing emphasis on urban vibrancy derived from social media data in recent years (Chen, Arribas-Bel, & Singleton, 2019; Tu et al., 2020; C. Wu, Ye, Ren, & Du, 2018). Gaining a comprehensive understanding of the ability of urban areas to maintain their vibrancy is vital for urban planners, policymakers, and researchers. This understanding enables them to examine how lively urban areas react to disturbances and devise strategies and policies that foster long-lasting vibrancy, strengthen urban resilience, and establish more sustainable urban settings for residents.

Built on these contexts, this study aims to utilise social media data to

assess the resilience of urban vibrancy in the context of the COVID-19 pandemic, through identifying urban areas with stronger urban vibrancy and exploring their spatial, temporal and functional transformations to illuminate its implication for urban planning and governance. To accomplish this goal, we have four analytical objectives to achieve: (1) to propose an analytical framework to discern vibrant urban areas using an advanced spatiotemporal clustering method, (2) to integrate multiple-sourced social media data to enhance the representation of identified urban vibrancy, (3) to unveil the resilience of urban vibrancy through visualising how its spatial, temporal and land use characteristics (i.e., contextual characteristics) evolved during the pandemic, and (4) to provide implications into urban planning and governance to improve their adaptability and resilience during public crises. The analytical framework was implemented in Inner London as the pilot study with a time span of three years from January 1, 2019, to December 31, 2021; it has great potential to be employed to measure urban vibrancy in other geographic contexts and in response to future public health and/or environmental crises.

2. Data

2.1. Study area and timespan

The research was conducted in Inner London for the following reasons. First, London is a cosmopolitan metropolis catering to a multitude of individuals worldwide, boasting a thriving culture, flourishing financial markets, captivating attractions, and vibrant social scenes. It exhibits a high volume of digital footprints with millions of geo-tagged Twitter and Flickr data annually, even amidst the COVID-19 pandemic. Second, London has implemented various policy restrictions in response to this global health crisis, rendering it an exemplary city for examining the efficacy of these policy interventions and the resilience of its urban dynamism. Most importantly, following the prior works conducted by (Chen et al., 2019; Lansley & Longley, 2016), a considerable amount of social media data has been aggregated solely within Inner London. Consequently, we exclusively chose Inner London as our study area to mitigate potential data bias arising from spatial heterogeneity. By focusing on Inner London, we aim to minimise the impact of spatial bias and ensure a more uniform distribution of data, thereby enhancing the reliability and validity of our analysis on urban vibrancy.

The timespan of data retrieval was from 2019.01.01 to 2021.12.31, covering the period encompass timeframe before the first national lockdown in England and the subsequent periods of lockdown along with the gradual easing of restrictions. During this three-year period, London experienced three lockdowns, which began on March 23, 2020, November 5, 2020, and January 6, 2021, as well as a series of policy restrictions and lifts to control the spread of the virus. This continued until July 19, 2021, known as 'Freedom Day', when most legal restrictions ended. The changes of policy measures in London enables a holistic understanding of the impact of the pandemic on urban vibrancy and the demonstrated resilience throughout this period.

2.2. Social media data

The social media data utilised in this study are primarily sourced from Twitter and Flickr, both of which extensively employ user-generated content and are easily accessible through public APIs (Chen et al., 2019; Lansley & Longley, 2016). Twitter functions as a micro-blogging platform that enables users to quickly compose textual messages. Flickr serves as a photo sharing platform that enables users to disseminate their photographs accompanied by the original timestamp. Given the inclusion of geo-tagging, both datasets offer rich spatial and temporal attributes, in addition to semantic information (Twitter) and visual contents (Flickr), thereby presenting substantial avenues for researchers to explore place representations, urban perception, human mobility, social events, public sentiment, trending topics, and more

(Chen, Liu, Arribas-Bel, & Singleton, 2022; Cheng et al., 2023; Lansley & Longley, 2016).

Social media data can be a sufficient proxy for urban vibrancy despite criticism on their inherent biases in spatial, temporal, and demographic aspects (e.g., activity-location mismatches, event-specific time frames, and prevalence among young, male, and well-educated users) (Huang et al., 2024). Its ability to capture real-time, user-generated content reflecting the dynamic nature of urban life helps to explain this (Chen et al., 2019; Z. Li, Wang, Emrich, & Guo, 2018; Shelton, Poorthuis, & Zook, 2015). The geo-tagged character of the data helps to precisely track human activity and movements, which can be used as a gauge of the vitality of various urban areas. Together with the semantic and visual content, the frequency and variety of posts provide insightful information on the activities people are engaged in, their emotions, and the attractiveness of particular locations (Chen et al., 2022; Lai, Cheng, & Lansley, 2017; Zheng, Capra, Wolfson, & Yang, 2014). Substantial quantities of social media activity serve as indicators of popular social venues, transportation centres, cultural gatherings, or commercial enterprises, so enhancing our overall comprehension of urban liveliness. Moreover, the time aspect of social media data allows for monitoring fluctuations in urban vibrancy over a period, providing significant observations on how different regions react to different occurrences or alterations in policies.

The utilisation of geo-tagged social media data typically requires more attention. First, this category of data does not represent the entire population or diverse demographic cohorts, thereby biasing the data towards certain demographics such as young and well-educated males or spatial bias of urban populations (Chen et al., 2019). Second, the data maybe dominantly influenced by highly active users who contribute more than others or specific transient and concentrated events, leading to spatial and temporal imbalances. Third, privacy and ethical concerns also warrant due deliberation during the collection and processing of data, as it has the potential to expose sensitive and personal details of individuals. To mitigate these concerns, we conducted a series of data pre-processing procedures to mitigate or eliminate the data bias associated with the nature of geo-tagged data.

More specifically, we initially integrated Flickr with Twitter to encompass a broader population and collected a prolonged three-year period to capture more spatiotemporal coverage. All data underwent meticulous processing with considerations such as diverse aggregations to safeguard user privacy. Additionally, multiple data cleaning steps were implemented to reduce certain outliers and user dominance to enhance the data reliability. To commence, individuals who posted multiple tweets or captured photographs simultaneously (accurate to the seconds) are highly improbable occurrences and are deemed outliers, necessitating the retention of only one record for each user. Subsequently, tweets or photographs posted for advertising or promotional purposes also qualify as outliers and should be excluded. Users who, on average, posted more than ten tweets or photographs per day over three years, significantly surpassing the typical average of two or three daily posts, are considered advertising accounts and should be filtered out. Tweets comprising solely of URL links are subjected to this advertising filter criterion as well. Thirdly, individuals who have contributed an extremely high number of records at the same location are omitted to mitigate the impacts of user dominance. This is measured by calculating the frequency of identical users posting at identical locations. Suppose the count number exceeds the standard deviation based on the count distribution. In that case, these individuals are identified as extraordinarily active users who would ultimately skew the results and are thus dropped from the dataset. Lastly, to further diminish temporal bias such as the influence of events occurring within specific weeks or months, we exclusively extract data posted on weekday and aggregate them into 24-hour intervals. This can aid in eliminating seasonal impacts and enable us to concentrate on consistent and robust urban vibrancy.

A total of 451,557 social media data were remained following the data processing phase. Fig. 1 displays the density distribution of social media

data through the implementation of a hexagonal visualisation, chosen for its advantage of providing a more uniform and precise representation of density across the map as compared to the normal grid-based map. These patterns within Inner London were visualised separately, one representing the period before the pandemic (Fig. 1(a)), and the other depicting the during-pandemic period (Fig. 1(b)), with respective data sizes of 308,016 and 143,541. Overall, social media data within both periods mostly located in the city centre (City of London and west of Tower Hamlets) and middle-west region of Inner London (east of Camden and Westminster), although the density slightly decreased during the pandemic. The spatial pattern shifted from clustered to scattered throughout the course of the COVID-19 pandemic.

2.3. Other datasets

In addition to the social media data, auxiliary data were also collected in this study, including London and Inner London boundaries data¹ provided by Greater London Authority; London Road network data² and Points of Interest (POI) data³ provided by Ordnance Survey (OS). The boundary data primarily establish the spatial extent for various data collections, while the road network data is used to construct the network-based service areas of the identified spatiotemporal centroids.

The POI data is an extensive directory that includes over four million records, covering both public and private establishments across Britain. This data, which is sourced and verified from more than 100 prominent listing suppliers and updated quarterly, includes diverse categories such as accommodation, eating and drinking, commercial services, attractions, sport and entertainment, education and health, public infrastructure, manufacturing and production, retail, and transport (Ordnance Survey, 2024). In our study, this dataset is used primarily for contextual enrichment, helping to reveal the functional attributes of the identified AOIs' catchments and to explain their resilience before and during the COVID-19 pandemic.

3. Method

3.1. Method framework

An extensive analytical framework was created to examine the resilience of urban vibrancy prior to and during the COVID-19 pandemic, as shown in Fig. 2. We employed a spatiotemporal clustering model to detect urban spatiotemporal areas of interest (ST-AOIs) based on the cleaned geo-tagged social media data. The notion of urban areas of interest (AOIs) is extended from our prior investigations (Chen et al., 2019, 2022; Y. Liu, Singleton, Arribas-bel, & Chen, 2021). The ST-AOIs function as indicators and representations of urban vibrancy by collecting activities that involve a large number of people. They offer vital insights into the ever-changing and dynamic nature of urban life.

These ST-AOIs, which can be interpreted as spatiotemporal concentrations of human activities, are crucial for comprehending urban vibrancy, as they reflect the spatial and temporal distribution of human activities. The most vibrant areas that attract the most activities are indicated by the spatial distribution, which includes the number, size, and coverage of ST-AOIs across various sections of the city. The temporal distribution of these ST-AOIs encompasses their duration, appearance, and disappearance times, which reveal patterns such as seasonal trends, peak hours, and variations over time. Furthermore, the

¹ London and Inner London boundaries: <https://www.data.gov.uk/dataset/f9e5c66f-954a-4633-af9a-081318726548/inner-and-outer-london-boundaries-london-plan-consolidated-with-alterations-since-2004>

² Road data: <https://beta.ordnancesurvey.co.uk/products/os-open-roads>

³ POI data: <https://www.ordnancesurvey.co.uk/business-government/products/points-of-interest>

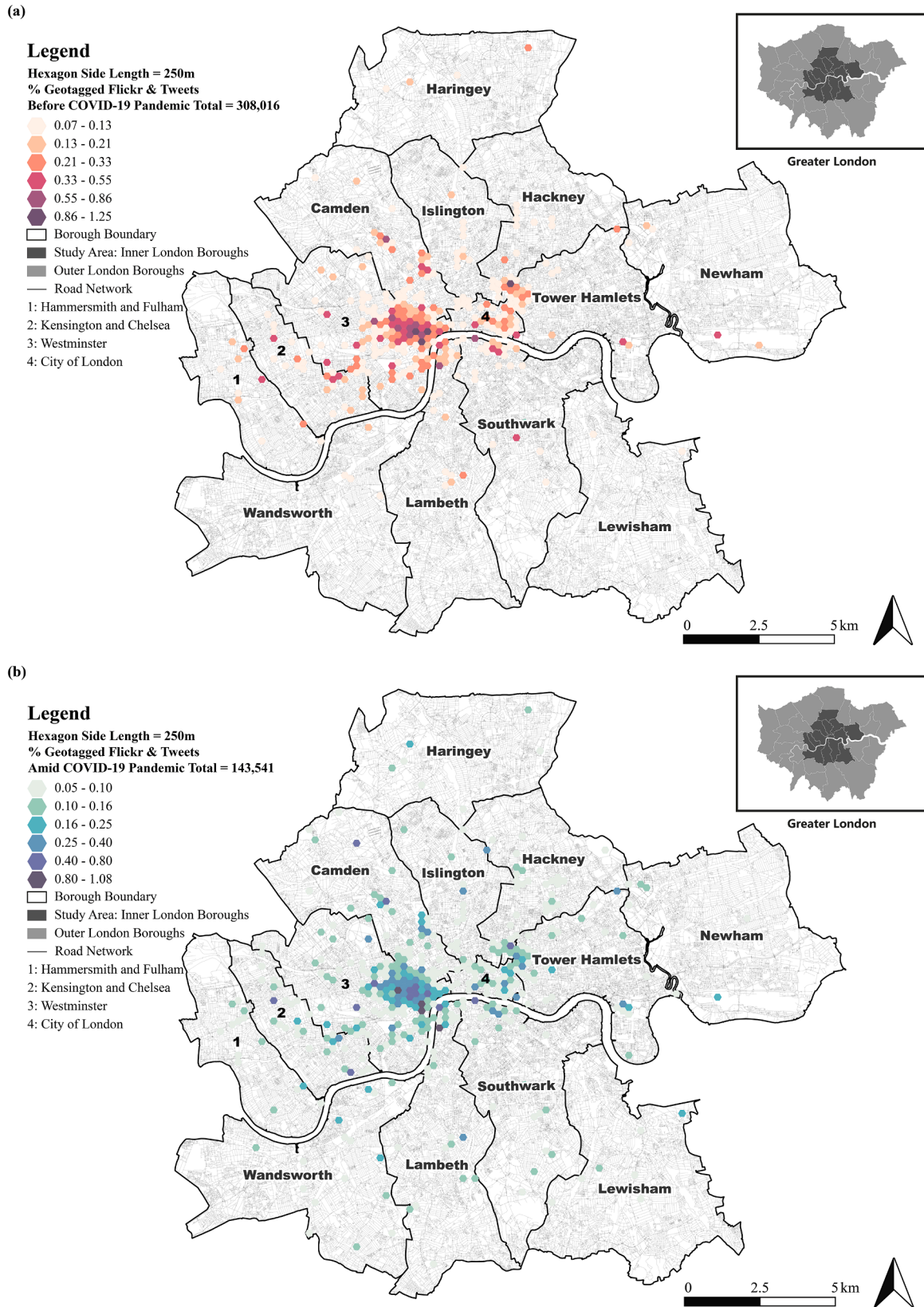


Figure 1. Hexagonal density map of geo-tagged social media data (Tweets and Flickr) in Inner London during (a) pre-pandemic and (b) peri-pandemic periods.

potential functional types of these areas, such as commercial centres, recreational spots, or cultural sites, can be inferred by contextualising the ST-AOIs with points of interest (POI) data. This thorough examination of spatial and temporal dimensions, which is substantiated by

contextual data, offers valuable insights into the resilience and vibrancy of urban areas, thereby influencing urban planning and policymaking.

One of the benefits of employing a spatiotemporal clustering model is its capacity to accurately identify patterns of human activity and

ST-AOI Detection

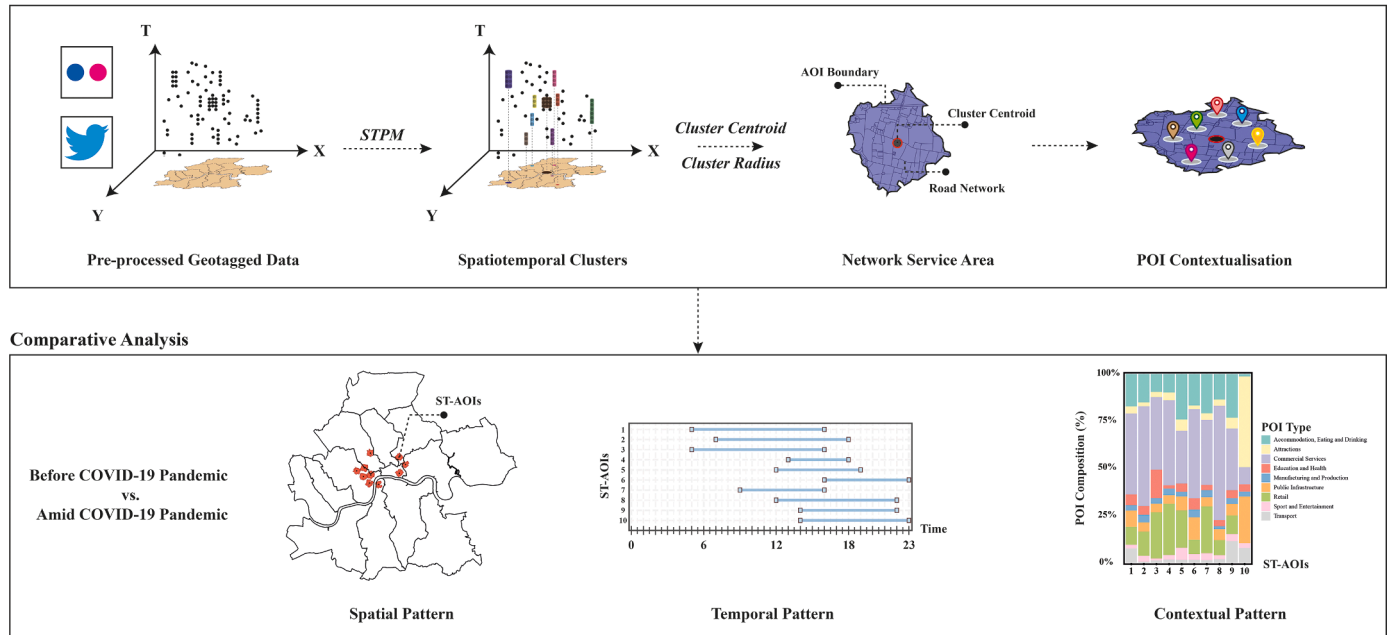


Figure 2. Analytical framework for investigating the urban vibrancy resilience before and during the pandemic.

urban dynamics over time and space, thereby facilitating a more sophisticated comprehension of urban vibrancy. This method is particularly well-suited for documenting changes resulting from the pandemic, as it enables the identification of hotspots of activity, their temporal evolution, and their spatial distribution. The spatiotemporal clustering model can be used to disclose the temporal appearances and spatial distribution of AOIs in the processed geo-tagged social media data, providing a comprehensive understanding of urban vibrancy.

We subsequently conducted a network analysis to determine the catchment areas for the ST-AOIs (i.e., service areas) by utilising the centroid and radius derived from the clustering model. The accuracy of spatial analysis is improved by the network analysis method, which provides a precise delineation of service areas based on actual road networks, rather than simple Euclidean distances. Finally, the place semantics of the ST-AOIs were quantified using POI data, which provided contextual information regarding the functional categories of urban vibrancy. By integrating POI data, we can enhance our comprehension of the characteristics and functions of vibrant urban areas, enabling a comprehensive analysis of the ways in which various categories of locations contribute to urban vitality.

In order to conduct a thorough examination of the resilience of urban areas, we interpreted ST-AOIs for both periods in three distinct dimensions: spatial, temporal, and functional. Spatial analysis is the process of analysing the geographic distribution of ST-AOIs to comprehend the distribution of urban vibrancy across various regions. Temporal analysis examines variations in the ST-AOIs across time, therefore capturing the dynamic character of urban vibrancy by means of pandemic-induced changes or trends. This involves examining the occurrence and length of AOIs, including those that show up during the daylight and vanish in the evening, therefore reflecting patterns of human activity. Functional analysis evaluates the activities and services that are represented within the ST-AOIs by utilising POI data to ascertain the extent to which different functional categories contribute to urban resilience. We can analyse the various constructive components for each identified ST-AOI through POI enrichment, taking into account their unique spatiotemporal patterns. This semantic enrichment of POI data allows us to understand the specific contributions of various activities and services to urban vibrancy.

This comprehensive methodology guarantees a thorough evaluation

of urban vibrancy and its ability to withstand challenges. The proposed methodologies in this study are applicable due to their ability to integrate diverse data sources and analytical techniques to provide a full view of urban vibrancy. The spatiotemporal clustering model depicts dynamic changes in human activity, the network analysis provides precise spatial delineation, and the POI data provides valuable contextual information. Collectively, these methodologies facilitate a comprehensive examination of urban resilience, rendering them particularly well-suited for investigating the consequences of substantial disruptions such as the COVID-19 pandemic.

3.2. ST-AOI identification

We employed the space-time permutation scan statistics (STPSS), a statistical and a spatiotemporal clustering technique, to identify ST-AOIs from large numbers of social media data. Unlike previously prevalent methods that typically rely on density-based spatial clustering methods such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) or its variants such as hierarchical DBSCAN and Multi-scaled DBSCAN (C. Cheng et al., 2021; S. Hu et al., 2020; X. Liu, Huang, & Gao, 2019), the STPSS also incorporates the temporal dimension into the clustering process, which holds significance when handling high-resolution space-time data, yet is frequently disregarded. The STPSS was originally proposed by (Kulldorff, Heffernan, Hartman, Assunção, & Mostashari, 2005) and designed to make minimal assumptions regarding the location, time, or size of the outbreak, aiming for early detection of disease outbreaks that only uses case numbers. The novelty of this approach lies in considering the joint distribution of events in both space and time, rather than treating them as independent dimensions. This has made it a valuable method in diverse domains such as environmental monitoring (Pereira, Caramelo, Orozco, Costa, & Tonini, 2015), epidemiology (J. Wang et al., 2014), transportation planning (Shen & Cheng, 2016) and criminology (Uittenbogaard & Ceccato, 2012).

The STPSS method was executed in the SaTScan software,⁴ comprising typically four stages. First, a case file and a coordinates file

⁴ The software is available from www.satscan.org.

are generated from the data with space-time attributes. Then, the scan sizes are determined for both spatial and temporal windows to identify clusters. For spatial window, supplementary alternatives are available to define shapes, either in the form of circles or ellipses. The magnitude of the scan window can be fixed or proportional based on various requisites. Since the number of geo-tagged posts for both Twitter and Flickr has largely decreased during the pandemic, proportional scan window was applied to mitigate this change on how people interact with the social media platforms. Following this, an appropriate threshold is selected to define the minimal case size for high-rate clusters that aids in ensuring a high frequency of occurrences. Finally, the confidence interval necessitates determination via p-values and only statistically significant clusters are retained.

In our instance, the number of cases for the case file pertains to the number of social media posts, and coordinates are obtainable from their geo-tagged information. Hourly aggregation was utilised as the temporal unit to discern more routine and robust ST-AOIs without the impacts of seasonal or transient events. The scan size determined for the spatial and temporal window, respectively, was no greater than half of the posts, confined within a circle with a radius of 400 m and spanning at least two hours. The strategy we designed aimed to detect relatively enduring areas within 10-minute walking distance from any given place to another (circa 800 m). This was inspired by the notion of a '10-minute city' that seeks to establish sustainable urban neighbourhoods where residents can access most of their daily necessities within a 10-minute walking or cycling from their homes - a concept that has gained widespread acceptance globally (Logan et al., 2022). The determination for the minimal size of cases was based on the most robust clusters generated by various percentages of social media data, ranging from 0.5% to 1% following exploratory data analysis. This enabled us to identify ST-AOIs during both the pre-COVID and peri-COVID pandemic periods, unaffected by the influence of disparities in the size of social media data. Lastly, clusters exhibiting p-values equal to or less than 0.1 were remained to identify the most statistically significant ST-AOIs.

3.3. Catchment construction and place contextualisation

The cluster results are depicted as diverse groups of points exhibiting spatial and temporal patterns. Each group encompasses supplementary spatial particulars regarding the cluster circles generated during the process of clustering. Our next step entailed executing service area analysis to construct catchments for ST-AOIs. The rationale behind this pursuit is twofold. Primarily, it enables further examination of place semantics by integrating POI point data into these ST-AOI catchments. Secondly, when juxtaposed with uniform circular shapes, service areas account for the actual distance or travel time required to reach a specific location, thereby presenting a more verisimilar depiction of urban vibrancy's accessibility.

Service area analysis is employed to identify the geographical coverage or catchments of a facility or service based on distance or travel time. This approach has found applications in numerous domains, including retail agglomeration (Dolega, Pavlis, & Singleton, 2016), healthcare planning (Jia, Wang, & Xierali, 2017), and public transportation optimisation (Velaga, Nelson, Wright, & Farrington, 2012). The process of delineating service areas typically necessitates the definition of three key elements: origin points, travel mode, and threshold(s) of travel time or distance. In our particular case, the origin points encompass a diverse array of centroids of ST-AOIs, the chosen travel mode is walking, and the thresholds manifest as the radiuses of ST-AOIs. Service area delineation was performed twice, both prior to and amidst the COVID-19 pandemic, to establish urban vibrancy catchments separately.

The ultimate step involved characterising each ST-AOI by allocating POI data to it. POI serves as a location-based directory facilitating the identification and categorisation of diverse places. It has emerged as a prominent data source for a multitude of applications, including urban

management (X. Zhang, Du, & Wang, 2017), tourism planning (Shao, Zhang, & Li, 2017), and marketing strategies (H. Li, Wei, Wu, & Tian, 2019), enabling a profound comprehension of the geographic landscape. In Great Britain, POI is classified into three hierarchical levels, comprising 9 groups, 52 categories, and 600 classes. These POI classifications were leveraged to calculate the proportion of each POI Group for ST-AOIs, both before and during the COVID-19 pandemic. Finally, a comparative analysis is employed to explore the dynamic changes and resilience (in this context, referring to adaptive capacity) of ST-AOIs through various aggregations within spatial, temporal, and contextual dimensions.

4. Results

4.1. Changes of urban vibrancy during COVID-19 pandemic

The changes of ST-AOIs across spatial, temporal, and contextual characteristics prior to and during the COVID-19 pandemic are illustrated in Fig. 3, 4 and 5 correspondingly. Fig. 3 presents a zoom-in map that reveals disparities in spatial patterns of all ST-AOIs. Blue catchments with circular centroids (A-Q) and red catchments with triangular centroids (a-i) denote distinct ST-AOIs identified during two separate periods. Prior to the onset of the pandemic, a total of 17 ST-AOIs were discerned, predominantly situated in the central and middle-western regions of Inner London. Most ST-AOIs (D-K) were found in the eastern portion of Westminster, followed by three ST-AOIs in Camden (A-C) and two in Kensington and Chelsea (L and M). The remaining four ST-AOIs (N-Q) were scattered around various boroughs, adjacent to the Thames River and City of London. Since the outbreak of COVID-19 pandemic, the number of ST-AOIs has dramatically decreased to nine, with many of them diminishing in Camden, Westminster and Kensington and Chelsea. Merely four ST-AOIs remained virtually unaltered, as their centroids exhibited extremely geographical proximity in both time periods. These ST-AOIs were concentrated in locations, namely St. Pancras International Rail Station in the borough of Camden (referred to as A and a), Bond Street in Westminster (referred to as E and c), Spitalfields Market in Tower Hamlets (referred to as N and g), and the financial hub in the City of London (referred to as O and h). Additionally, a novel ST-AOI (f) was identified southwest of Hackney, while the remaining ST-AOIs were situated in the eastern part of Westminster (referred to as D and b, G and e, J and d) and the northern part of Lambeth (referred to as Q and i), exhibiting significant spatial overlay in between the two periods.

The Fig. 4 depicts the temporal characteristics of each ST-AOI before (a) and amid (b) the pandemic. In general, no individual ST-AOI was exclusively active during the morning hours, with the majority exhibiting a higher level of vibrancy in the afternoon and evening. These patterns remained unaltered during the pandemic; however, they have become more diverse and ephemeral compared to the pre-pandemic period. The four spatially and virtually unaltered ST-AOIs (A and a, E and c, N and g, O and h) also exhibited similar temporal patterns in Fig. 4 that maintained heightened urban vitality during daylight hours, particularly in the afternoon. The newly identified ST-AOI (f) showcased its vibrancy for a duration of 9 h, spanning from 11:00 to 20:00. Among the overlapping four ST-AOIs (D and b, G and e, J and d, and Q and i), only ST-AOI G and e, located in the vicinity of Chinatown and Covent Garden in Fig. 3, could be deemed as robust ST-AOIs due to their entirely consistent temporal patterns, which exhibited heightened vibrancy during the evening and night from 18:00 to 23:00.

The contextual characteristics are displayed in Fig. 5, wherein the x axis represents the percentage distribution of nine POI groups for each ST-AOI before (a) and during (b) the pandemic. It illustrated that commercial services consistently dominated most ST-AOIs, followed by retail, or accommodation, eating and drinking during both periods. Nevertheless, ST-AOIs with larger proportions of retail, attractions, and public infrastructure (e.g., referred to as B, C, K and L) were more

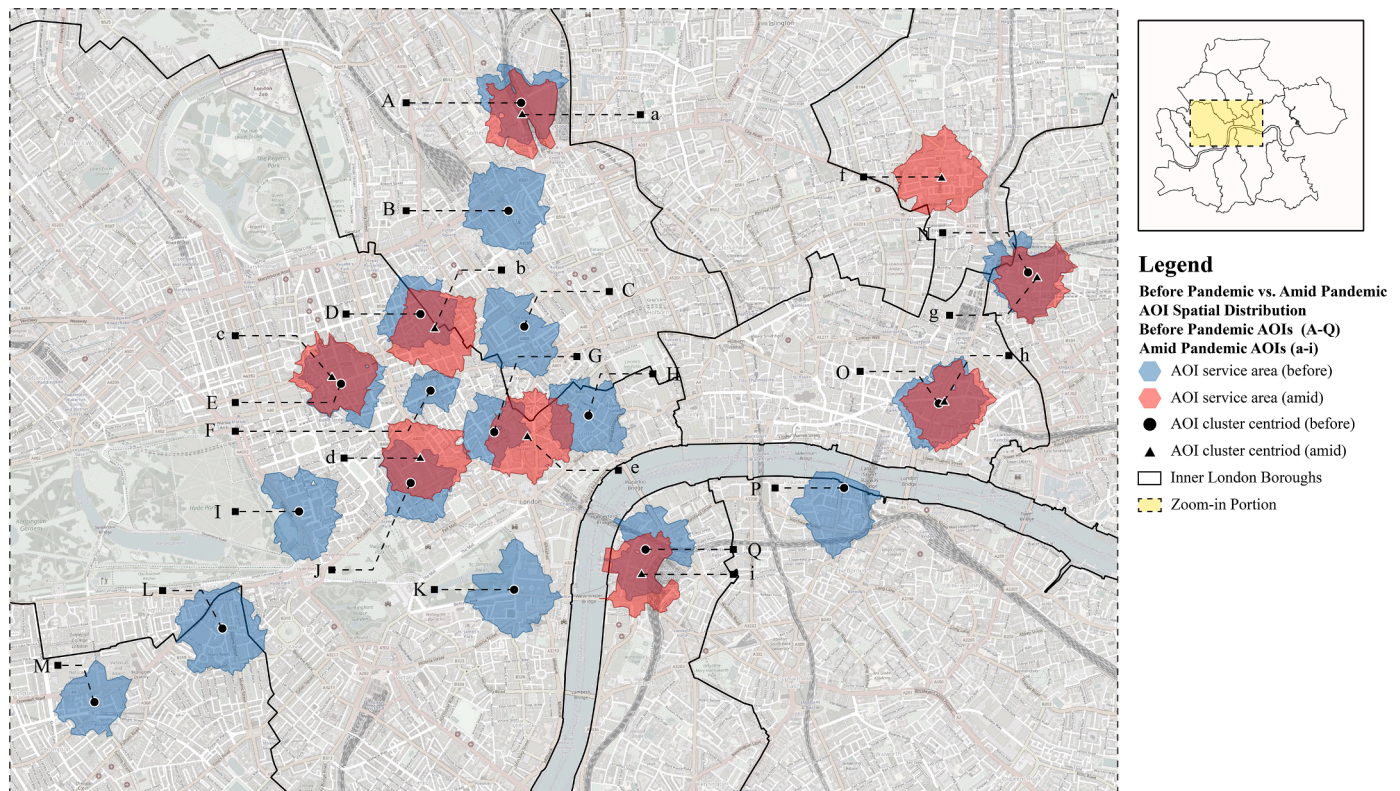


Figure 3. Spatial disparities of ST-AOIs in Inner London before the pandemic (denoted by A, B, C...) and during the pandemic (denoted by a, b, c...).

susceptible to the disruptions caused by the pandemic. Specifically, four spatiotemporal consistent ST-AOIs again exhibited similar contextual characteristics. They primarily encompassed indispensable urban functionalities such as pivotal public transportation services (A and a), fundamental healthcare facilities (E and c), eating and drinking establishments (N and g), and significant commercial services (O and h). These vibrant urban areas tended to demonstrate greater adaptability and resilience when confronted with the outbreak of the COVID-19 pandemic. Regarding the newly identified ST-AOI f, its distinctive contextual characteristic was the larger proportion of public infrastructure predominantly consisting of charitable organisations during the pandemic. The ST-AOI G and e, which has been deemed robust ST-AOI spatially and temporally, also showcased its consistency in contextual characteristics, comprising larger proportions of sports and entertainment, as well as eating and drinking.

4.2. Holistic temporal and contextual disparities during COVID-19 pandemic

To gain a deeper comprehension of the adaptive capacity inherent in urban vibrancy, we further consolidated the temporal and contextual characteristics of ST-AOIs to compare their disparities in the pre- and peri-pandemic periods. The holistic temporal changes of ST-AOIs are illustrated in Fig. 6, where the x axis represents the percentage of frequency count for each hour, while the y axis denotes the hours ranging from 0 to 23. Before the pandemic, the temporal patterns of urban vibrancy exhibited a smooth transition and displayed an approximate normal distribution, reaching their peak between 14:00 and 18:00. However, when the COVID-19 health crisis emerged, the disparities in urban vibrancy became more pronounced between consecutive hours, as evidenced by the fact that the count for the hour of 11:00 was twice that of the hour of 10:00. Additionally, the peak hours shifted to an earlier and shorter time frame (11:00–14:00). These changes in vibrant time were likely attributable to government-imposed restrictions on human

mobility, indoor gatherings, entertainment venues, and operating hours (Santillo, 2022), resulting in the consolidation of vibrant time primarily during midday and early afternoon. Nevertheless, the existence of a minimum of four hours of vibrant time still ensured a commendable adaptive capacity at this juncture.

The holistic changes of contextual characteristics of ST-AOIs were explored and visualised in Fig. 7, where the dots with various colours denote the percentage decrease of nine POI groups and purple line represents their average percentage decrease since the COVID-19 pandemic. The overall count of all POI groups experienced a substantial decline due to the identification of fewer ST-AOIs during the pandemic. The category of transportation was the most profoundly impacted, undergoing an approximate 50.5% precipitous downturn. Attractions, public infrastructure, and sports and entertainment were subsequent categories that exhibited a decline surpassing the average percentage decrease (around 33.4%). The categories of commercial services and eating and drinking registered decreases of approximately 24.5% and 27.1%, respectively, exhibiting a comparatively lower levels of impact compared to other POI groups.

5. Discussion

Our key findings unveil that vibrant urban areas with distinct common characteristics tend to exhibit greater resilience in exposure to the COVID-19 pandemic. The spatial distribution of these areas is typically situated in central urban neighbourhoods that are enriched with essential amenities and services, such as transportation hubs (e.g., international rail station), educational and healthcare facilities (e.g., health establishments), eating and drinking places (e.g., diverse restaurants), and commercial services (e.g., financial centre). The transportation hubs play a critical role in maintaining connectivity and accessibility (Amirzadeh et al., 2022), educational and healthcare facilities provide essential services that support the wellbeing and stability of the community (Afrin et al., 2021), the concentration of diverse

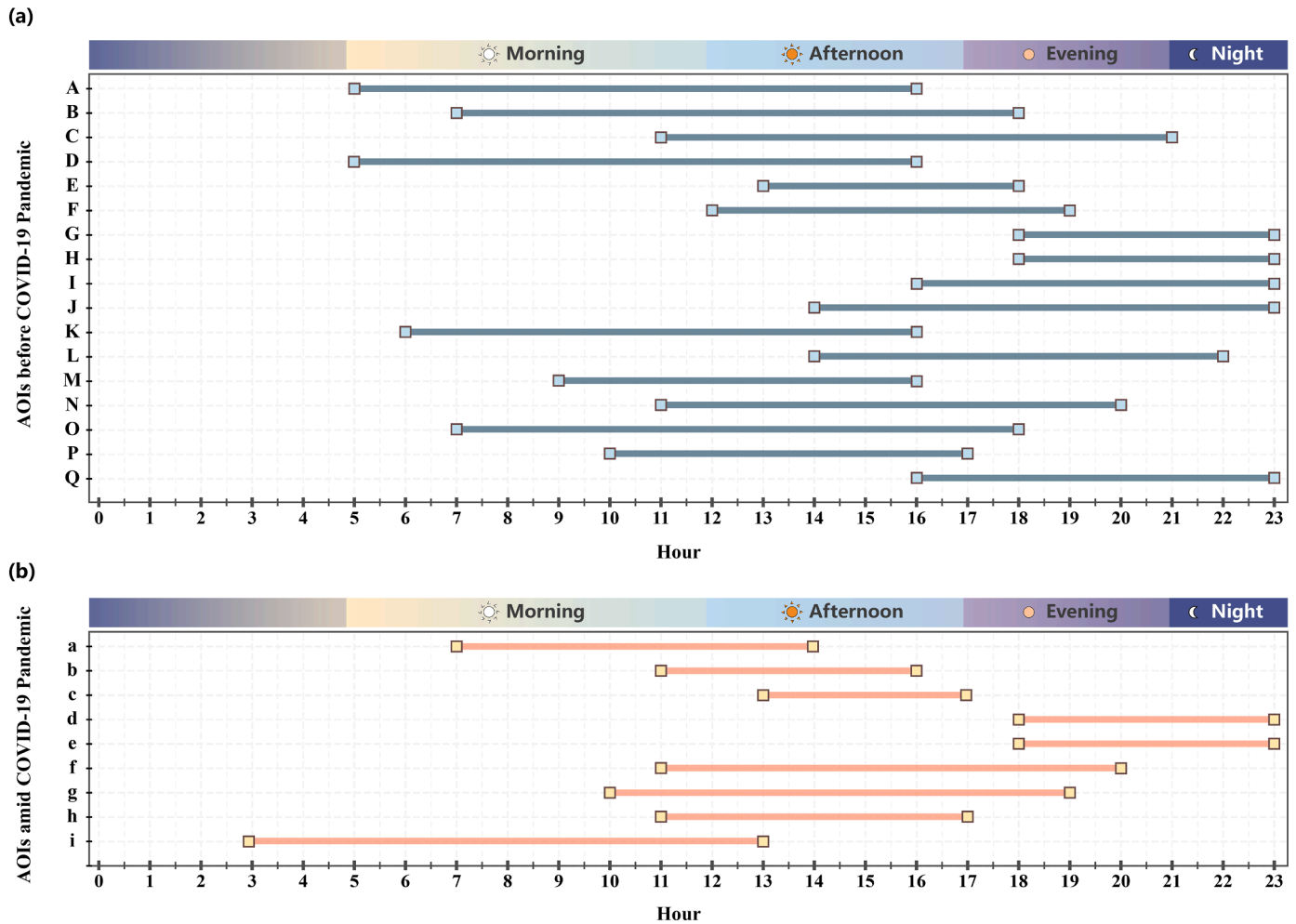


Figure 4. Temporal Characteristics of ST-AOIs before and during the pandemic. (a) The temporal distribution of ST-AOIs before the COVID-19 pandemic. (b) The temporal distribution of ST-AOIs during the COVID-19 pandemic. The length of each line indicates the duration of the ST-AOI, while the square markers denote the start and end times. The colour gradient represents different times of the day: Morning, Afternoon, Evening, and Night.

eating and drinking establishments fosters social interaction and economic activity (Florida, Rodríguez-Pose, & Storper, 2023), and commercial services ensure economic stability and facilitate business continuity (Meerow et al., 2016). These attributes collectively create a dynamic and resilient urban environment, highlighting the importance of integrated policymaking that prioritizes the development of multifunctional and well-connected urban spaces.

Furthermore, according to the work of (B. Wang, Loo, Liu, Lei, & Zhou, 2024), the reliability of urban vibrancy results can be validated by an external dataset. Hence, an official area classification, which is an Output Area Classification (OAC) covering England and Wales using Census 2021 data, is utilised for comparison. The validation results display that urban areas with more vibrancy are characterised by adult residents aged between 25 and 44 who lived in high density central neighbourhoods and are well-educated and professional. This aligns with the demographic characteristics of most social media data, further demonstrating its capability and flexibility in capturing urban vibrancy.

The temporal characteristics of urban vibrancy, particularly the higher vibrancy in the afternoon, fit past research stressing the afternoon as a crucial time for social and economic events in urban settings (Arribas-Bel, 2014). This is usually the result of a mix of elements including lunch breaks, shopping hours, and social events usually set around these times. The flexibility in temporal patterns found in our study implies that vibrant urban areas are not only able to sustain activity but also shift active periods from seven hours (i.e., 12:00–18:00)

before the outbreak to four hours (i.e., 11:00–14:00) in response to changing conditions. These areas' capacity to sustain a minimum of four hours of vibrancy every day shows a strong social and economic foundation supporting ongoing activity despite external disruptions.

Contextually, transport was the most significantly affected POI group during the pandemic, presumably as a result of policy restrictions, the increased fear of virus transmission, and the transition to remote working arrangements and local travel (Bick et al., 2023; Jenelius & Cebecauer, 2020). Attractions also faced significant repercussions due to mobility restrictions as illustrated by (Casado-Aranda, Sánchez-Fernández, & Bastidas-Manzano, 2021). Numerous attractions, such as Big Ben, Westminster Abbey, and St. James Park, which primarily attract tourists from other cities or countries, saw significant declines. The pandemic's impact on tourism underscores the vulnerability of urban vibrancy in areas heavily reliant on external visitors, highlighting the need for diversified urban economic activities. In contrast, commercial service establishments, which were widely dispersed throughout Inner London and were notably concentrated in vibrant urban areas, demonstrated a greater ability to adjust to disruptions caused by public crises and emergencies. As noted by (Florida et al., 2023), the spatial distribution of these commercial services across the city also contributed to the maintenance of a level of vibrancy. They also discuss the significance of local business ecosystems in supporting urban economies during crises. Furthermore, places with strong urban vibrancy, notably in the field of eating and drinking, have demonstrated

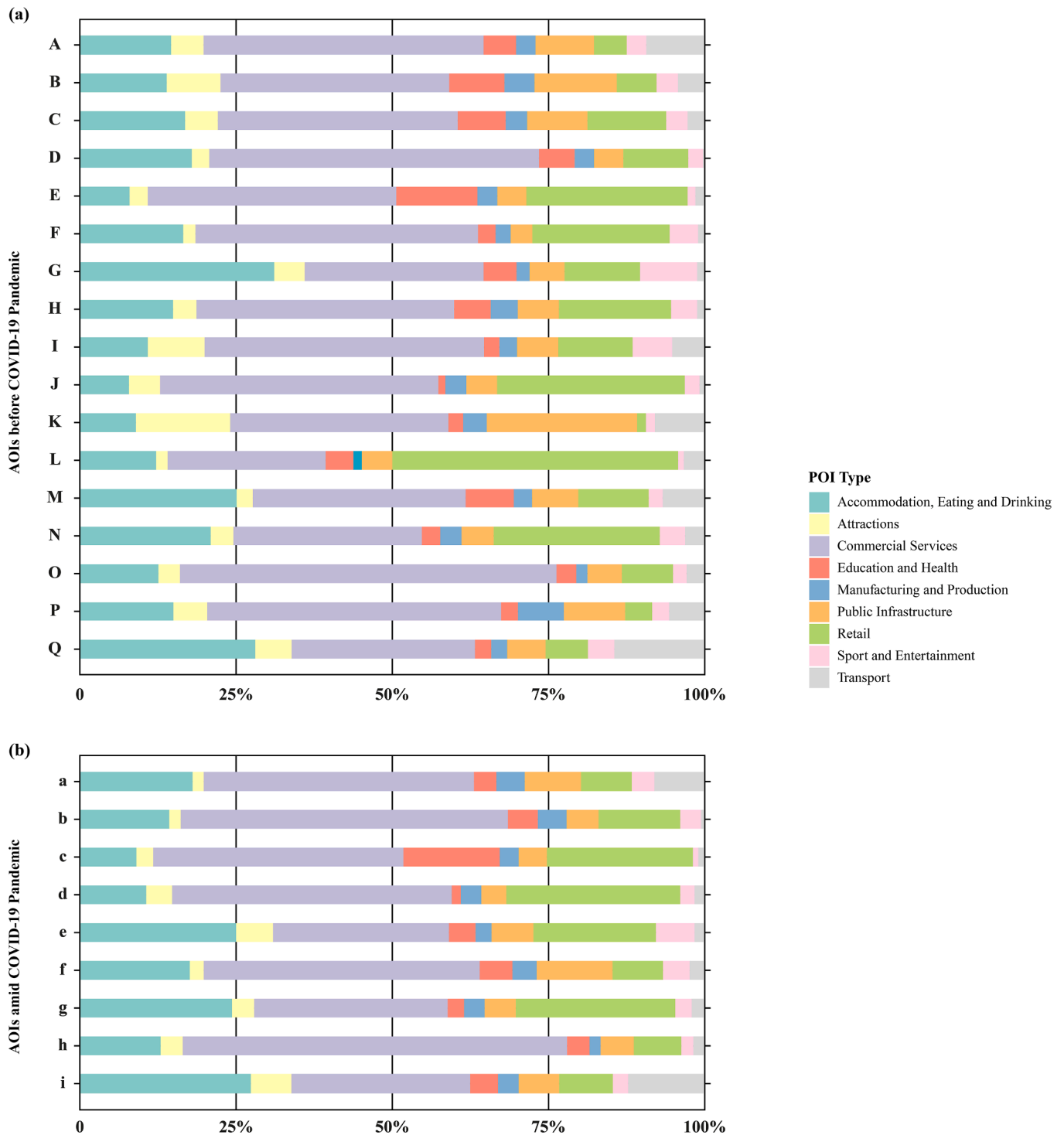


Figure 5. Variation of contextual characteristics (POI types representing functional characteristics) of ST-AOIs before and during the pandemic.

remarkable recovery and resilience, despite barriers such as venue closures during lockdown and tiered limitations. The food and drinks sector's resilience were backed by a hospitality strategy issued in the UK in July 2021 (Kwasi & Scully, 2021), which intends to help the sector rebuild stronger and more robust by providing takeaway, delivery, and outdoor dining options. These adaptive solutions not only helped companies survive, but also contributed significantly to the preservation of urban vibrancy by providing inhabitants with ongoing access to essential social and economic activities.

The resilience capacity of vibrant urban areas during the pandemic

may be attributed to their diverse economic base, instantly adaptive strategies, social fabric, strong community networks, and robust digital infrastructure. These factors, as highlighted in the work of Jacobs (1961), who emphasised the importance of diversity of urban areas and their inhabitants' ability to adapt to and support each other through crises. The economic diversity and adaptability found in more vibrant places let operations be flexible. For example, cafes and restaurants were modified by providing takeaway and outside dining options. Maintaining activity levels by means of mutual help, local businesses, and community projects that keep the places lively and resilient likely depends

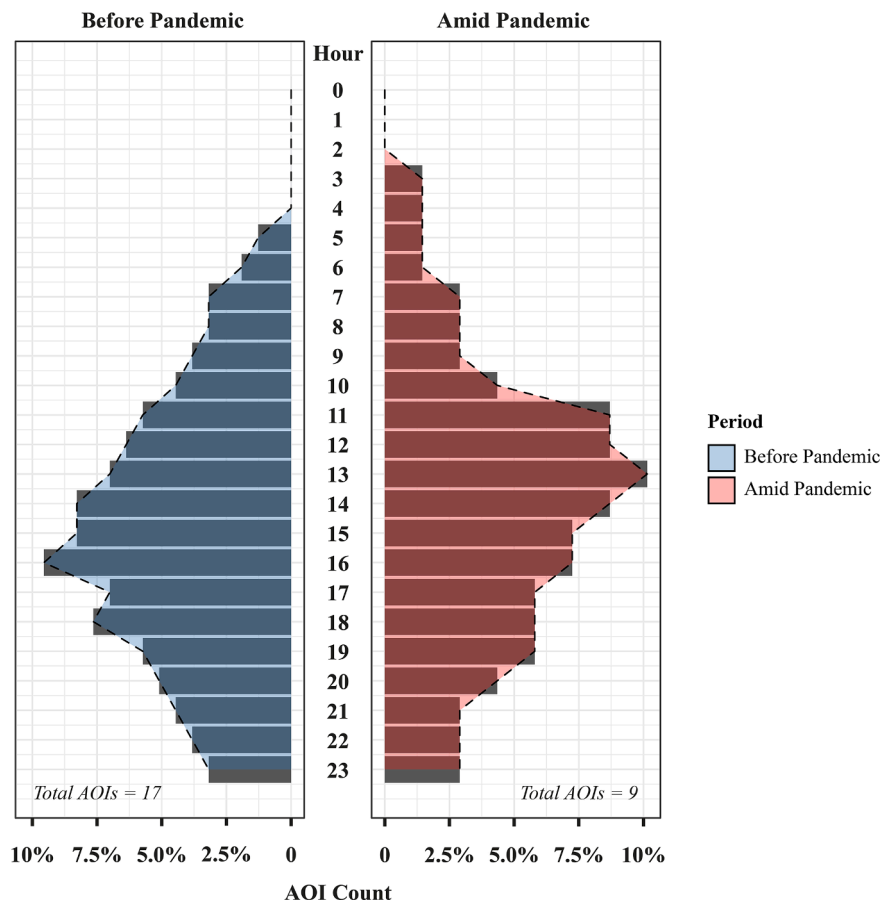


Figure 6. Changes in aggregated temporal patterns before and during the pandemic.

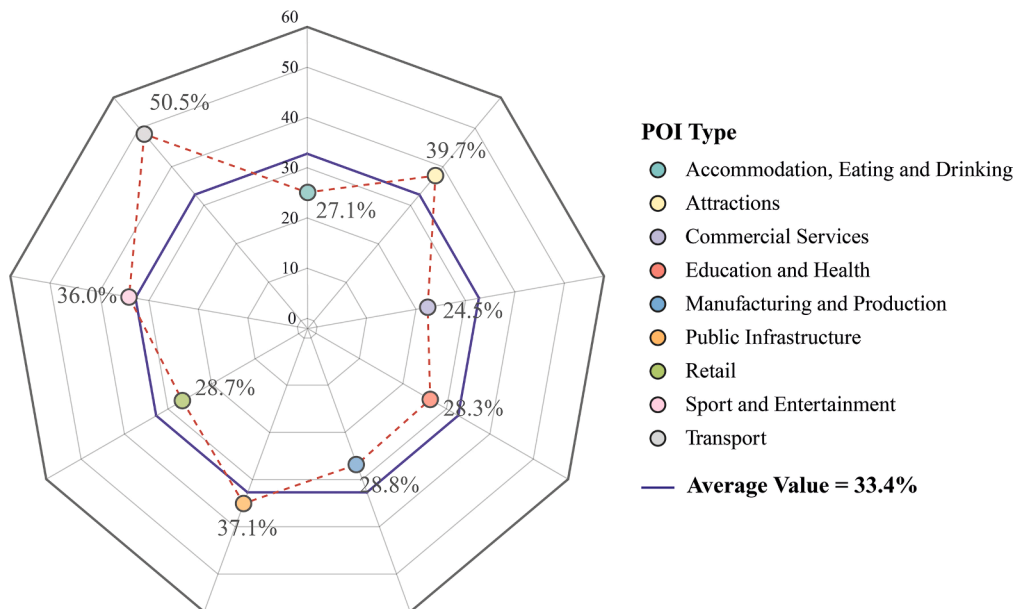


Figure 7. Overall decrease percentage of each POI group during the pandemic, with the dark blue line indicating the average decrease (33.4%).

on the strong social networks and community support inside these active areas. High degrees of digital infrastructure made it possible to move smoothly to virtual social contacts and remote work. This digital adaptation guaranteed that social and economic events could go on, therefore lessening the whole influence of physical constraints. Ultimately, the

existence of well-designed public areas such as parks, pedestrian zones, and open-air markets made it possible for safer outside activities—which were absolutely vital for preserving urban vitality during the epidemic. These results offer a strong basis for comprehending and improving urban resilience in normal conditions post-COVID-19 and

against next public crises.

Our research also has far-reaching policy implications concerning sustainable urban planning and governance to promote adaptability and resilience in a post-pandemic world. By identifying inner-city areas that have experienced the least impact on urban vibrancy during the COVID-19, we contribute to an in-depth knowledge about urban space and the shift of human behaviours at the aggregated level, providing insights to inform crisis-adaptive urban planning and policy. The resilience of urban areas against future disruptions may be improved by promoting mixed-use development that incorporates transport hubs, educational and healthcare facilities, eating and drinking places, and commercial services. Policies that encourage economic activity and social interaction, such as those that encourage outdoor dining and delivery services during crises, may thereby preserve urban vibrancy by supporting local businesses. Furthermore, the resilience that was observed during the upheaval may be further enhanced by investing in reliable public transport and ensuring that essential services are accessible in central urban neighbourhoods. These strategies are consistent with the literature that underscores urban diversification and local business ecosystems in the sustainability of urban economies (Florida et al., 2023; Jacobs, 1961; Kwasi & Scully, 2021). Moreover, the validation of social media data as a reliable tool for monitoring urban vibrancy underscores the potential for innovative data-driven approaches in urban governance, facilitating real-time responses to emerging challenges and contributing to the creation of resilient, sustainable cities.

This study advances the literature with its distinctive contributions as follows. First, we propose an innovative methodological framework to identify, track, and analyse the spatiotemporal and land use changes of urban vibrancy before and during the pandemic. This framework clusters urban vibrancy by simultaneously considering spatiotemporal attributes of data, which surpasses numerous existing studies that solely employ spatial density of individuals to cluster urban areas of interest (Chen et al., 2019; Y. Hu et al., 2015). With similar data availability, the framework can be applied to various metropolitan areas to unveil patterns of urban vibrancy across diverse urban morphologies and can be utilised to assess the impact of future public crises and emergencies on urban vibrancy. Second, our analyses employ multi-sourced social media data, specifically Twitter and Flickr, to improve the data representativeness and coverage that was rarely considered in prior works on urban vibrancy based on social media data (Tu et al., 2020; C. Wu et al., 2018). Third, our results illuminate the resilience of urban vibrancy, which might be difficult to monitor via traditional data and methods (e.g., (Chu et al., 2021; X. Hu et al., 2022; Valenzuela-Levi, Echiburu, Correa, Hurtubia, & Muñoz, 2021)). More importantly, it examines the changes of urban vibrancy caused by the COVID-19 pandemic as a systematic interruption to the human society as a whole—providing spatially and temporally explicit evidence for urban planners and governors in urban rejuvenation and restoration initiatives. These aspects have not been thoroughly explored in previous studies on urban vibrancy or in the use of social media data to understand the impacts of COVID-19 (Cui et al., 2022; S. Wang et al., 2023).

6. Conclusions and limitations

In summary, this study offers a thorough analysis of the effects of the COVID-19 pandemic on urban vibrancy in Inner London, offering urban planners and governors valuable insights to enhance the adaptability and resilience of urban vibrancy during public crises. We suggest an analytical framework that utilises a combination of multiple social media data sources to identify vibrant urban areas and investigate their spatial, temporal, and contextual characteristics in the context of the pandemic. Our framework surpasses conventional studies that exclusively depend on the spatial density of observations by considering multiple dimensions. The study reveals that urban spaces situated in central urban neighbourhoods and enriched with essential amenities and services tend to exhibit greater resilience in the face of disruptions.

It elucidates the temporal patterns of urban vibrancy, particularly the shift in active periods from pre-pandemic to pandemic times, showcasing the adaptability of vibrant urban spaces. Furthermore, it assesses the varying resilience capacities of different POI groups, such as transportation, attractions, commercial services and eating and drinking, in maintaining urban vibrancy amid the pandemic.

This research has certain limitations that can be further explored in future studies. First, an inherent drawback of using social media data as a proxy of urban vibrancy lies in its demographic bias. The elderly, children, and individuals who abstain from employing smart devices or participating in social media platforms are often excluded from this dataset, constraining the comprehensive population representation of the research findings. Future identification of urban vibrancy could address this by incorporating survey-based data for broader populations representation. Second, our study does not link the opening time of POI groups (e.g., commercial services) with the identified stronger periods of urban vibrancy, thereby casting doubt on the accuracy of the land use contexts associated with urban vibrancy. This aspect could be enhanced in future endeavours by considering opening hours as a factor to bolster the reliability of the results. Thirdly, this study overlooks the post-pandemic period, which generally commences in 2022–02 when the UK government introduced its new plan on ‘Living with COVID’ (Santillo, 2022). This is because Twitter API no longer supported free access since February 9, 2023 (GOTFREDSEN, 2023), limiting our ability in continuously accessing the newest 2022 Twitter data. Using other social media data to replace Twitter data may mitigate this limitation by including 2022 data as well to provide further implications regarding the long-term resilience of urban vibrancy. Last but importantly, future works could also focus on the driving factors behind changes of urban vibrancy via robust modelling techniques, such as built environment (e.g., design of buildings, green and blue space, and street views) and demographic and socioeconomic characteristics of neighbourhoods (e.g., ethnicity, age, and income levels), to better understand how urban spaces can adapt to future challenges.

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CRediT authorship contribution statement

Meixu Chen: Writing – review & editing, Writing – original draft, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yunzhe Liu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Zi Ye:** Writing – original draft. **Siqin Wang:** Writing – review & editing, Writing – original draft. **Wenjing Zhang:** Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data availability

Data will be made available on request.

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