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Mobility Vitality in Active and Micro-Mobility Modes: Measuring Urban Vitality Through Spatiotemporal Similarity

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Abstract. Urban vitality captures the dynamic and interactive nature of city environments by highlighting how residents engage with public spaces, making it essential for differentiating neighborhoods. Traditional indicators focused on static measures, such as density, land-use diversity, and built environment design. Most of these measures fail to capture the dynamic nature of vitality. This paper introduces the concept of *Mobility Vitality*, a novel measure that captures the dynamic and vibrant nature of human activities through the analysis of active and micro-mobility modes, including biking, e-scootering, and recreational running. Taking Washington, D.C. as a case study, we analyze the spatiotemporal patterns of mobility across different modes and time periods, revealing significant variations in mobility patterns between the downtown core and peripheral areas. The results also indicate that the most unique time series of the three micro-mobility modes are weekend mornings and weekday nights, and fluctuations are more pronounced within a day than between weekdays and weekends. The proposed analysis framework may guide infrastructure investments, optimize urban transport networks, and advance more equitable and sustainable cities.

Submission Type. Analysis

BoK Concepts. Spatial Simulation Modeling, Open Science, and Geospatial Citizenship.

Keywords. Mobility Vitality, Urban Vitality, Micro-Mobility, Active Mobility, Urban Planning, Sustainable Cities, Spatiotemporal Analysis

1 Introduction

Urban Vitality refers to the dynamic and vivid quality of the urban environment, reflecting the use and experience of spaces by residents (Jacobs, 1961). This is an important measure that could be used to distinguish neighborhoods, evaluate policy impacts, guide urban planning, enable proper development, and create social, economic, and cultural exchanges.

A key aspect of urban vitality is the movement of people, especially through active and *micro*-mobility modes like running, biking, and e-scooters. These sustainable transport options operate at a human scale, promoting direct interactions with the city and enhancing community bonds. Research has shown that such modes increase physical activity (Lai et al., 2022), reduce carbon emissions (Nocerino et al., 2016), and support healthy lifestyles (Nieuwenhuijsen, 2020), thereby contributing to urban vitality and community cohesion.

Urban vitality already encompasses various indicators that reflect the liveliness and functionality of city spaces. We propose *Mobility Vitality* (MV), a dynamic aspect of urban vitality, evaluating how different modes of transportation use the roads over time. It examines whether a road consistently supports diverse transportation modes or is predominantly used by a single mode. A road with high mobility vitality not only experiences a high volume of trips but also exhibits a high mixture of transportation modes. This diversity in mobility patterns enhances accessibility, promotes sustainable transportation, and contributes to the overall dynamism of urban life.

Unlike traditional static indicators like density or land use diversity (Montgomery, 1995), in this study, we take shared micro-mobility and active modes as examples to reflect fluid movement patterns, varying by time and location. This approach provides urban planners with deeper insights into how various transportation modes are used in combination, enabling more effective urban planning decisions. It highlights inequities in transport access and makes sure mobility options are equitably distributed.

Herein, we contribute mainly to a methodological extension with the MV measure. In developing the measure, we use a sample of data that involves running, cycling, and e-scootering. This is not to say that these are the only forms of mobility that can be used to measure MV—in fact, we encourage researchers, planners, and policymakers to develop and assess their city's own MV through the use of their own data sources. The purpose of this work is to present the preliminary framework of MV and demonstrate its use with our own example set of mobility data.

With these objectives in mind, we will address the following three research questions (RQ) in this work:

RQ1 *Do different modes of local mobility exhibit different spatial and temporal patterns across a city?*
We address this question by examining trip volume at the scale of road segments, time resolution of a typical week, and across four modes of mobility. Through this analysis, we reveal where and when the commonalities and differences in mobility mode usage occur, providing insights into the spatial and temporal dynamics of urban mobility. Although it's a relatively simple question, it is important to set this baseline before continuing.

RQ2 *How do the four mobility modes differ in their spatiotemporal variability, and within each mode, which time series stands out as most unique? How do these variations compare across different time scales?*
We are asking four subquestions in this part: Among the four active and micro-mobility modes, which mode exhibits the highest degree of spatiotemporal variability? Additionally, within each mode, which time series demonstrates the most unique spatiotemporal mobility pattern? Do spatial and temporal differences manifest more across various time series within a single day or when comparing the same time series on weekdays versus weekends? To address this, we introduce the *Spatio-Temporal Alignments* (STA) (Janati et al., 2019) method, which aligns two time series to quantify differences in both spatial distributions and temporal sequences.

RQ3 *How can we combine different spatial and temporal mobility signatures to produce a Mobility Vitality measure that can be used to identify and compare different regions in a city?*
To address this question, we propose an approach for developing a combined MV measure. We will demonstrate how urban and transportation planners can utilize such a measure to compare different regions within a city.

The remainder of this paper is organized as follows: Section 2 reviews related work on urban vitality and mobility analytics. Section 3 describes the datasets and preprocessing steps. Section 4 introduces our methodological framework, providing a detailed explanation of how each of the three research questions is addressed. Section 5 presents the results of our analyses. Finally, Section 6 discusses the broader implications, limitations, and future research directions, followed by concluding remarks in Section 7.

2 Related Work

Vitality, also referred to as vibrancy, represents an essential urban quality arising from a diversity of activities (Lynch, 1984), and is largely reflected in its ability to attract commercial and pedestrian activities (Gehl, 1987; Wu et al., 2018). In recent decades, the availability of large-scale built environment data, such as OpenStreetMap (OSM) (Haklay, 2010), land use mix (Lu et al., 2017), detailed information on buildings and blocks (Sung and Lee, 2015), and points of interest (POIs) (Zeng et al., 2018), heralded a new era of quantitative analysis using big data in urban vitality research (Liu et al., 2015). However, these datasets are relatively static and still cannot reflect real-time changes in urban vitality.

In recent years, more and more scholars have begun to use all kinds of spatiotemporal data in mapping urban vitality. Examples include night lighting remote sensing data (Zhang et al., 2021; Xia et al., 2020), mobile phone signaling data (Wu and Niu, 2019; Li et al., 2020), social media check-ins (Li et al., 2022b; Yue and Zhu, 2019), Baidu heat maps (Dong et al., 2022), and small catering business data (Ye et al., 2018). As data collection and analysis advanced, scholars began integrating diverse sources to create multidimensional urban vitality frameworks (Liu and Shi, 2022) and compare vitality across cities (Yue et al., 2021).

However, using origin-destination (OD) or trajectory data as a proxy for urban vitality is still uncommon. Most studies that rely on single-dimension measures do not capture mobility vitality. For example, researchers have used metro trips (Sulis et al., 2018), bike-sharing flows (Zeng et al., 2020), car-hailing activities (Zhang et al., 2020), and taxi flows (Chen et al., 2022; Zhang et al., 2022) to assess urban vitality.

Recent studies have combined mobility data with other sources to create multidimensional urban vitality measures. For example, Kang et al. (2021) used POIs, taxis, and mobile data; Li et al. (2022a) combined taxis, bike-sharing, and reviews; Yang et al. (2023) merged Baidu OD trips and Dianping reviews to differentiate tangible and intangible vitality; Qiang and McKenzie (2023) compared metro, taxi, and bike; Tu et al. (2022) utilized metro cards and social media in three different cities. More importantly, an increasing number of researchers are focusing their attention on active mobility. Qiu et al. (2024) estimates exercisality on urban trails based on three types of trajectories: walking, running, and cycling. Zhu et al. (2024) matches walking and running trajectories with the six visual indicators from street view and then analyzes the gender and age differences in these two exercise preferences.

Although the last two studies incorporate various active mobility modes, Qiu et al. (2024) only examines a limited number of running trails, whereas Zhu et al. (2024) focuses on exploring the running preferences of different demographic groups rather than assessing the vitality that active mobility represents. Furthermore, except for work by Yang et al. (2023), all other analysis units are either neighborhood, block, or grid level, which lack spatial granularity and do not align with the inherent characteristics of the movement, as it happens on the streets. Last, previous efforts to utilize diverse mobility data for depicting urban vitality have proven insufficient. Therefore, conducting multidimensional MV analyses at the street level that include active mobility remains an under-explored area and is urgently needed.

3 Data

To demonstrate our MV approach, we conduct an example study in Washington, District of Columbia (D.C.), using data from four mobility platforms. We obtained *Capital Bikeshare* (CB) trip data, including OD and timestamps, from the city's public portal[1]. Additionally, we accessed Lime's dockless e-bikes and e-scooters data, referred to as *Lime Bike* (LB) and *Lime Scooter* (LS), via their public API[2]. For the year 2023, we analyzed 1,329,016 LB trips, 2,703,025 LS trips, and 4,467,334 CB trips. Recreational running trajectories were sourced from *Strava*[3] between 2011 and 2022, focusing on the top 10 *segments*[4] in D.C., resulting in 10,109 runs with GPS trajectory data, timestamps, and duration. Here, we utilized Strava data to analyze running trajectories in Washington, D.C., over a span of ten years rather than concentrating solely on the year 2023. This approach was necessitated by the comparatively smaller size of the Strava dataset when compared to shared micro-mobility datasets. We believe that aggregating data across a decade does not compromise the validity of our analysis, as prior research indicates that human mobility patterns exhibit a high degree of spatiotemporal consistency (Gonzalez et al., 2008).

Before analysis, trips were restricted to durations between two minutes and 24 hours. For CB, LB, and LS data, we calculated the shortest path on D.C.'s roadway network[5] using trip origins and destinations[6], then derived trip speeds. Trips exceeding the maximum speeds for bikes and scooters, as well as Lime vehicle recharging trips, were excluded (McKenzie, 2019). Strava data were cleaned by removing invalid trajectories (e.g., unrealistic speeds, large GPS gaps, and durations over 6 hours) and limiting them to one trajectory per athlete to reduce bias.

[1] https://s3.amazonaws.com/capitalbikeshare-data/index.html
[2] https://ddot.dc.gov/page/dockless-api
[3] https://developers.strava.com/docs/reference/
[4] Parts of a road or trail over which athletes compete for fastest travel time.
[5] https://opendata.dc.gov/datasets/DCGIS::roadway-block/about
[6] Using the Python packages 'networkx' and 'scipy.spatial.KDTree'.

After cleaning, shortest path trajectories were used to aggregate trip counts per road segment across the four mobility modes for eight time-day periods: four five-hour periods each for weekdays (WD) and weekends (WE) (6 am–10 am, 11 am–3 pm, 4 pm–8 pm, and 9 pm–1 am). The 2 am–5 am period was excluded due to low cycling and running activity, as shown in Fig. 1.

4 Methodology

Here, we analyze our urban mobility patterns at the road segment level across our four mobility modes and eight time periods. First, we examine road similarity across the city using trip volume as a measure. Next, we examine similarities in mobility patterns over both space and time employing the STA methodology. We then combine these insights to develop our mobility vitality measure that highlights differences and similarities across city road segments. Finally, a method for visualizing the spatiotemporal variability of mobility vitality is presented.

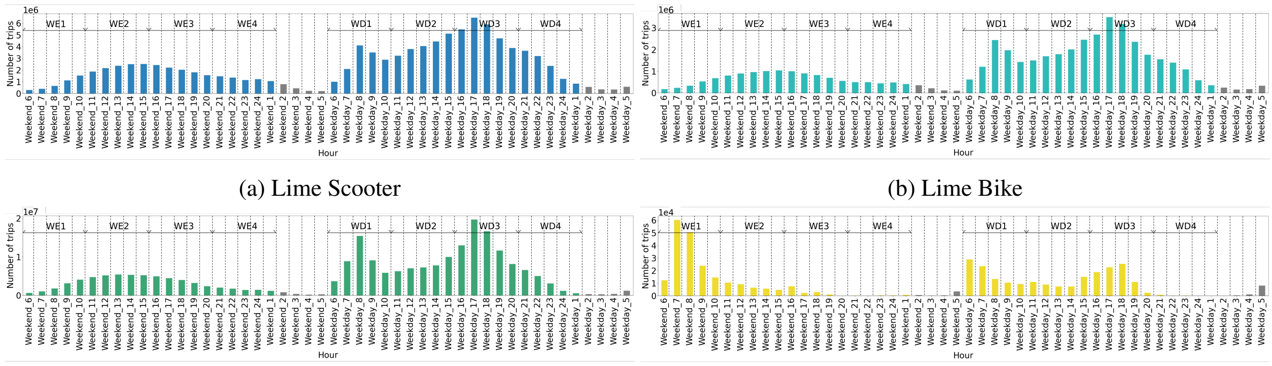
4.1 Trip Volume and Road Similarity

To address `RQ1`, we used cosine similarity to measure how different mobility modes exhibit spatial and temporal patterns. Each road segment's trip volume across eight time periods was normalized and compared. For each mobility mode, the cosine similarity between road segments determines their uniqueness. We then combined trip volumes across all modes into a 32-period array (4 modes $\times$ 8 time periods) to assess overall mobility patterns. Roads with high volume but low similarity were identified as popular and unique, while roads with high volume and high similarity were identified as common but less distinctive.

4.2 Spatio-Temporal Alignments

To address `RQ2`, we employ the STA method (Janati et al., 2019) to quantify differences between spatiotemporal series by simultaneously aligning their spatial distributions and temporal sequences. This approach enables nuanced comparisons of urban mobility patterns, effectively capturing complex variations across multiple transportation modes and diverse time periods.

The spatial component of our analysis is based on the distribution of trip counts across the city. Our analysis segments the city into a 50$\times$50 grid. This was necessary as STA requires grid data, similar to an image, with horizontal and vertical alignment. Additionally, running the analysis directly on thousands of road segments would have been computationally prohibitive. Thus, a 50$\times$50 grid size was chosen after testing a variety of grids ranging from 5$\times$5 to 100$\times$100. The dissimilarity measure converged at 50$\times$50, indicating that this grid size provided sufficient spatial resolution.



(a) Lime Scooter

(b) Lime Bike

(c) Capital Bikeshare

(d) Strava Running

Figure 1. Bar charts for hourly trip counts aggregated to weekends and weekdays for four mobility modes. Hours are grouped into four periods per day (WE1-4 and WD1-4).

We should also clarify the time series data structure in STA. As discussed earlier, the concept of a ‘time period’ refers to a 5-hour span during which all trips are aggregated. In contrast, a series consists of five individual 1-hour timestamps. For each timestamp, trip counts are normalized by dividing the trips in each grid cell by the total trips across the city for that hour.

Then, the STA method combines the Wasserstein distance for spatial dissimilarity and dynamic time warping (DTW) for temporal alignment. For two spatial distributions $\mathbf{x}$ and $\mathbf{y}$, the Wasserstein distance (Kantorovich, 1960) is:

$$W(\mathbf{x},\mathbf{y}) = \min_{\mathbf{P}} \sum_{i,j} \mathbf{P}_{ij}\mathbf{M}_{ij} \tag{1}$$

where $\mathbf{P}$ is the transport plan, and $\mathbf{M}_{ij}$ is the cost matrix based on geographic distance. Entropy regularization (Cuturi, 2013) is used to minimize the cost.

DTW aligns two time series by minimizing alignment cost, allowing for temporal shifts. STA uses DTW with the Wasserstein distance, with the STA cost defined as:

$$\text{STA}(\mathbf{X},\mathbf{Y}) = \min_{\mathbf{A}} \sum_{(\mathbf{x},\mathbf{y})\in\mathbf{A}} W(\mathbf{x},\mathbf{y}) \tag{2}$$

where $\mathbf{X}$ and $\mathbf{Y}$ are two time series and $\mathbf{A}$ is a feasible alignment of the two time series. In our case, each time series has 5 timestamps, so $\mathbf{A}$ is a path from $(1,1)$ to $(5,5)$. Each step of the path aligns one timestamp from series $\mathbf{X}$ and another from series $\mathbf{Y}$, with spatial distributions $\mathbf{x}$ and $\mathbf{y}$, respectively. The STA cost is the sum of the Wasserstein distance between $\mathbf{x}$ and $\mathbf{y}$ at each step, minimized over all possible alignments $\mathbf{A}$.

The STA matrix can be used to analyze many aspects of the spatiotemporal patterns. The uniqueness of each time series is quantified by the sum of its corresponding row, while the overall average variability for a mobility mode is captured by summing all matrix elements.

4.3 A Measure of Mobility Vitality

To address `RQ3`, we need a classification method to combine the various similarity properties that we have identified across the different mobility modes, time periods, and road segments.

For each time period, we divided the trip volume for each mobility mode into low volume (represented by ‘L’) and high volume (represented by ‘H’) based on its median trip volume. Hence, four modes in total, two classes for each, resulting in 2^4 possible combinations for the road segments. For example, ‘LLLH’ means one road has low LS, low LB, low CB, and high ST for a specific period. The ranking and spatial distribution of these categories fluctuate every second in real-time, representing the active and micro-mobility vitality of the city. And four periods were chosen to exhibit the representative MV result according to the highest and lowest similarity periods resulting from the STA analysis. Additionally, we compared the categories across these four time periods for each road to determine if the road segment retained the same category or varied in its categories across the four periods. This allows MV users to better understand the habits of cyclists and runners using the same road at different times of the week. Furthermore, this allows us to identify if a road is consistent in how cyclists, scooter-riders, or runners use it.

4.4 Data and Software Availability

The CB dataset is published as open data and can be downloaded from https://capitalbikeshare.com/system-data. As a result, the whole CB analysis is reproducible. Due to the terms of use and for privacy preservation, we are unable to share the raw trip data from Lime or Strava. Instead, we have provided the identifiers and scripts that can be used to ‘re-hydrate’ the trips.

Historical data for Strava is accessible, so we include a list of activity IDs for the runs. Yet, due to the API rate limit of 300 requests per hour, retrieving the approximately 10,000 activities used in our study would require a significant time investment. For the Lime data, trips are collected in real-time from the Lime API, but historical data cannot be obtained retrospectively if collection did not begin in 2023. Therefore, to reproduce a similar analysis for LS/LB, a researcher would need to run our script at regular intervals (e.g., every minute) over several months to a year and then reconstruct the trips following the documentation outlined in the GitHub link below.

All analysis scripts for STA, as well as the code used to generate the results and figures presented in this paper, are included in the GitHub repository at https://github.com/ptal-io/Mobility_Vitality.

5 Results

In this section, we present the results of our analyses, highlighting key insights into the spatiotemporal patterns of mobility vitality in Washington, D.C. First, we examine the overall trip volumes and identify distinctive road segment usage across multiple mobility modes. Then, we delve into detailed spatiotemporal alignments using the STA method, uncovering the most unique temporal series and mobility modes. Finally, we synthesize these findings into our proposed Mobility Vitality measure, visualizing the combined spatial distributions and highlighting the heterogeneity among different mobility modes to provide actionable insights for urban planners and policymakers.

5.1 Trip Volume and Road Similarity

Fig. 2 presents the analysis of trip volume and road segment similarity, showing that high-volume and unique patterns are dispersed around the U.S. Capitol, Lincoln Park, and H Street Corridor, rather than the National Mall (light pink regions to the right side of the National Mall shown in Fig. 2b).

Fig. 4 shows the four individual mobility modes, combining trip volume and cosine similarity to categorize road segments. Red roads represent unique temporal patterns, while blue roads show common, highly frequented routes, as defined in Section 4.1.

LS, LB, and CB have the highest trip volumes in downtown D.C., extending along primary roads (Fig. 4a - Fig. 4c), with patterns resembling the overall distribution in Fig. 2a. ST data (Fig. 4d) differs, with running activity concentrated along park paths, river, and mountain like Sixteenth Street Heights, National Arboretum, and Mount Pleasant.

Road similarity in Fig. 4a - Fig. 4c shows variation: areas like Massachusetts Ave NW exhibit high similarity, while places such as the National Mall, West Potomac Park, and Capitol Hill show low similarity. ST shows a similar pattern (Fig. 4d), but unlike the other three modes, contrasts between similarity and volume are scattered throughout both the inner and outer parts of D.C.

In addressing `RQ1`, we find substantial spatial and temporal differences between mobility modes. LS and LB exhibit similar patterns, while recreational running shows distinct spatial and temporal behavior across D.C. Above all, docked bikeshare is mostly concentrated in Downtown, while dockless systems offer a broader distribution, particularly extending further into the northern part of D.C.

5.2 Spatio-Temporal Alignments

The STA analysis shows that ST exhibits the greatest spatiotemporal variability, while LB shows the least. Fig. 5 presents the STA matrices for each mobility mode across eight time periods. WE4 and WD4 of ST were too sparse for reliable results and were excluded. Each matrix visualizes how usage patterns differ between periods, with higher values indicating greater discrepancies and lower values indicating more stable usage. The sums in the last column identify the most and least distinctive periods. Among the three shared mobility modes, the most distinctive time series are WE1 (weekend mornings) and WD4 (weekday nights), whereas running exhibits its highest uniqueness during WE3 (weekend afternoons).

For LS, LB, and CB, WE2, WE3, and WD3 show the least variability. ST, however, exhibits the highest variability during WE3. Like the others, ST also shows high variability during WE1 and low during WE2. Overall, WE1 is distinctive for all four modes, and WE2 is the least. Among the four modes, ST shows the highest variability, followed by CB, with LS and LB tied for the lowest.

To compare variability at different time scales, we averaged STA distances across three comparisons: within weekdays, within weekends, and between matching time periods on weekdays and weekends. As shown in Figure 5, we average the six pairwise distances among WE1, WE2, WE3, and WE4 (red cells) and similarly for weekends (green cells) to capture within-day variability, while the four distances between corresponding time periods (orange cells) capture cross-day variability. Table 1 shows that for the three micromobility modes, variability is highest within weekdays, followed by weekends, with the smallest differences observed between weekdays and weekends. In contrast, running exhibits the highest variability on weekends, then between weekdays and weekends, and the lowest variability within weekdays.

Table 1. Average of STA values across different time scales

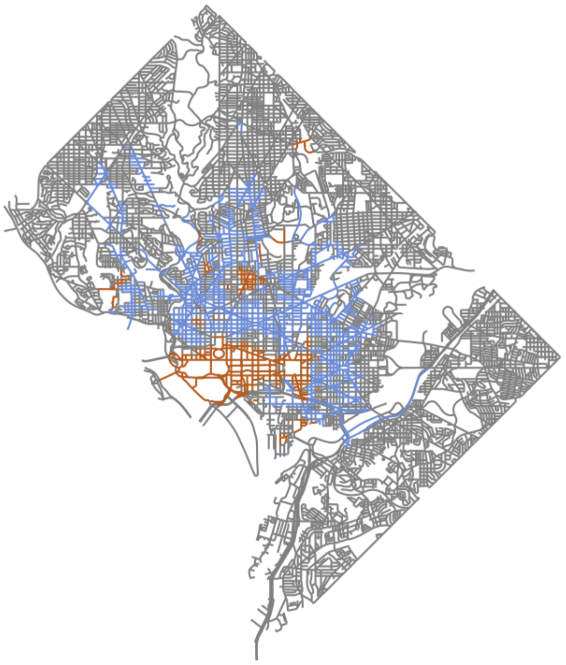
	Different times within WE	Different times within WD	Same time between WE and WD
LS	2.5	3.1	0.8
LB	2.2	2.9	0.9
CB	3.9	4.6	1.6
ST	12.3	5.9	6.6

(a) Total trip count for all mobility modes

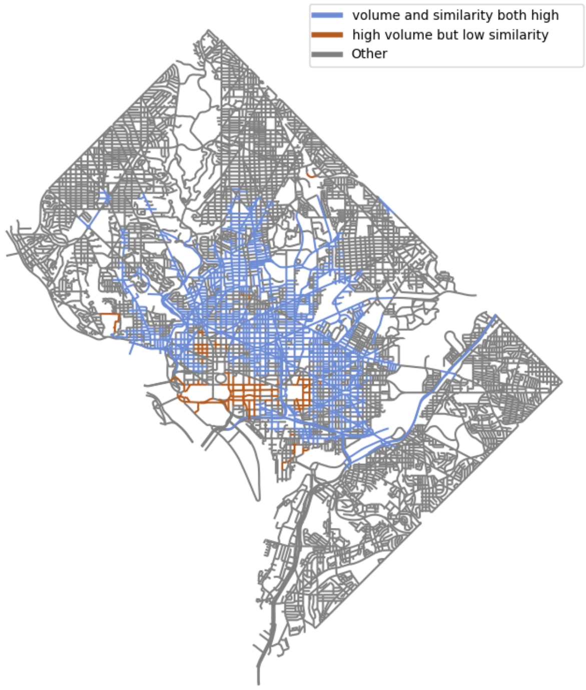
(b) Cosine similarity sum for all mobility modes

Figure 2. Trip volume and cosine similarity analysis with all mobility modes combined together shown for each road segment in Washington, D.C.

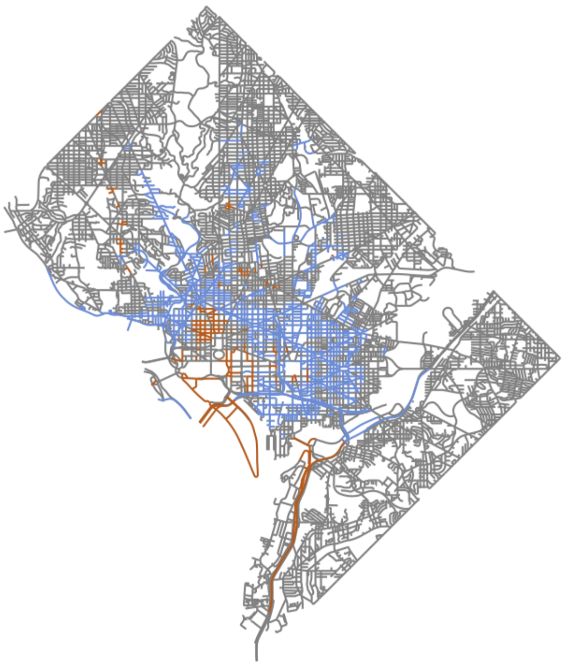
Figure 3. Reference map of Washington, D.C. showing neighborhoods discussed in the results



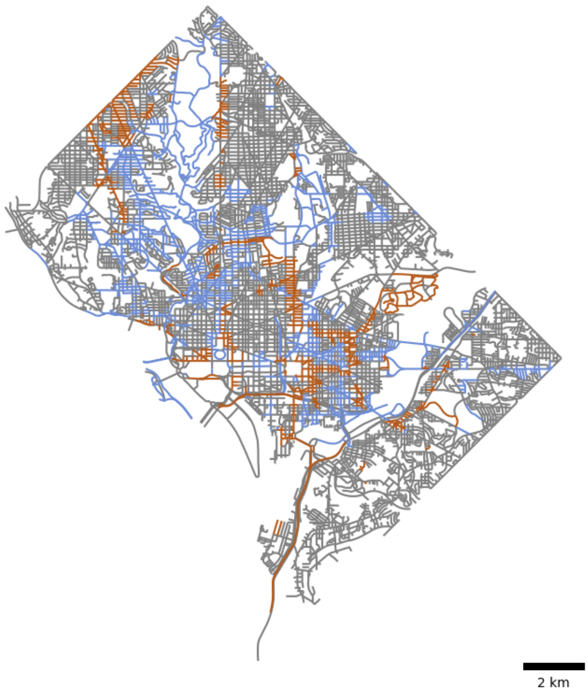
(a) Lime Scooters



(b) Lime Bike

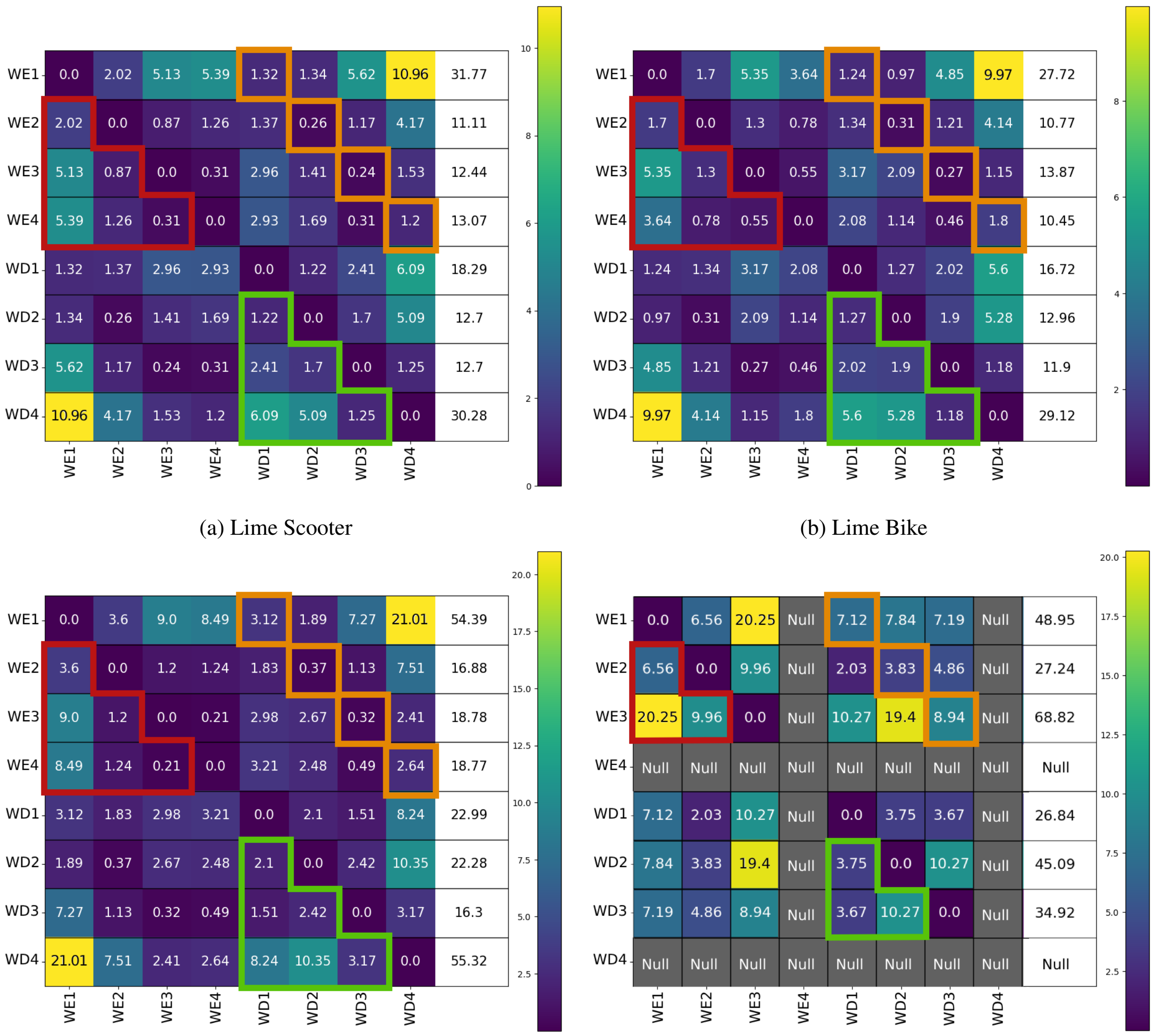


(c) Capital Bikeshare



(d) Strava Running

Figure 4. The combination of trip volume and similarity for each mobility mode. In this figure, any volume or similarity in the top 30% is considered high, while those in the bottom 30% are considered low. These illustrate the differences or coherence between trip volume and road similarity for different regions of Washington, D.C.



(a) Lime Scooter

(b) Lime Bike

(c) Capital Bikeshare

(d) Strava Running

Figure 5. STA distance matrices showing the results of the spatio-temporal alignment analysis. Higher values indicate greater differences in the mobility patterns. The last column of each figure shows the sum of the STA results for each time period row. The values enclosed by red (green) grid lines compare different time series within weekdays (weekends) and those enclosed by orange grid lines compare the same time series between weekdays and weekends.

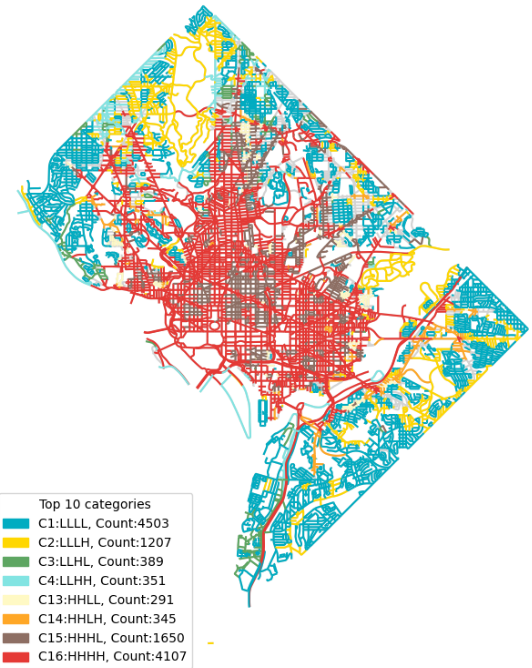
5.3 Mobility Vitality

Using the results of our STA analysis, we were able to identify the most representative time periods (lowest STA) and the most unique time periods (highest STA).

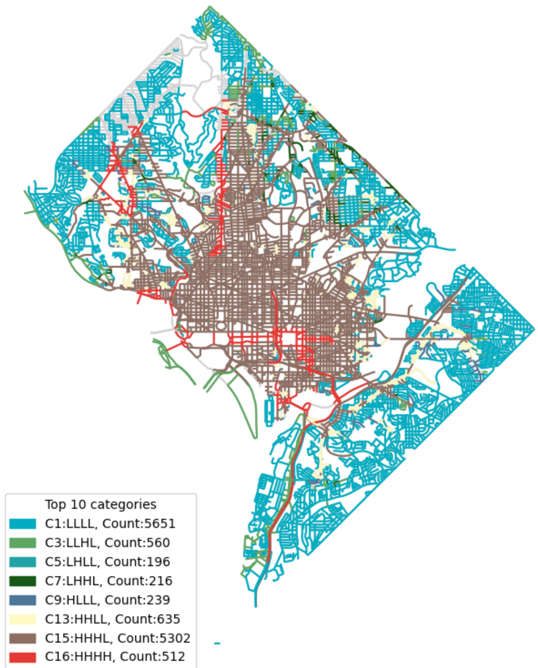
In addressing RQ3, we combine the results of the different spatiotemporal analyses to capture holistic patterns of how people move within D.C. We specify which roads are the most popular during different periods and which roads are dominated by a specific mobility mode. In examining Fig. 6, we can see that cyclists and runners use D.C.'s road network differently at different times[7]. On weekend mornings (WE1), a higher proportion of people choose to run downtown compared to weekend afternoons (WE3). During weekday afternoons (WD3), a higher percentage of people prefer running downtown compared to the same time period on weekends. However, at night, the number of runners in the downtown core sharply declines, except near the National Mall, whereas the frequency of downtown travel by the other three modes is still high during the evening. Nevertheless, the areas around the National Mall and 16th St NW consistently attract the highest percentages of users across all four modes, regardless of the period.

When discussing yearly trip volume, roads that are popular with at least three modes are almost all concentrated in downtown, whereas roads with low usage across all four

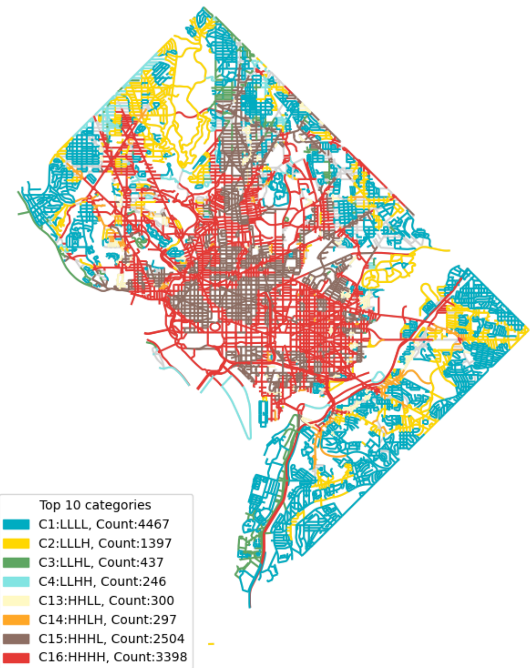
[7]For clarity, only the top 10 categories of four periods are shown in the map.



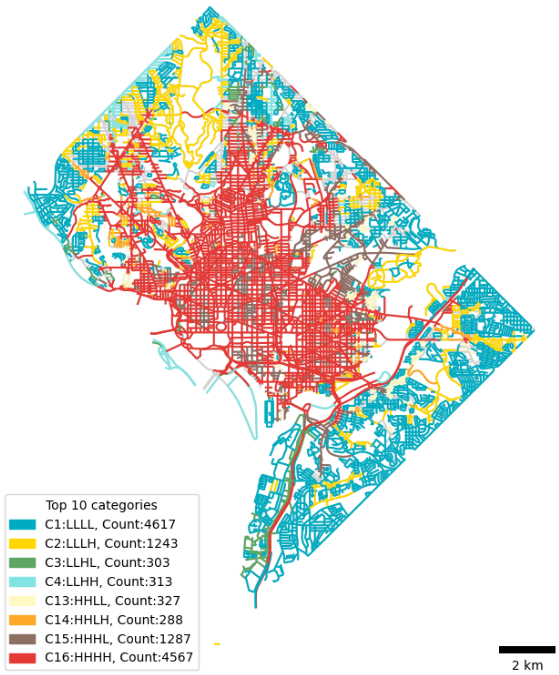
(a) Weekend Morning (WE1)



(b) Weekday Night (WD4)



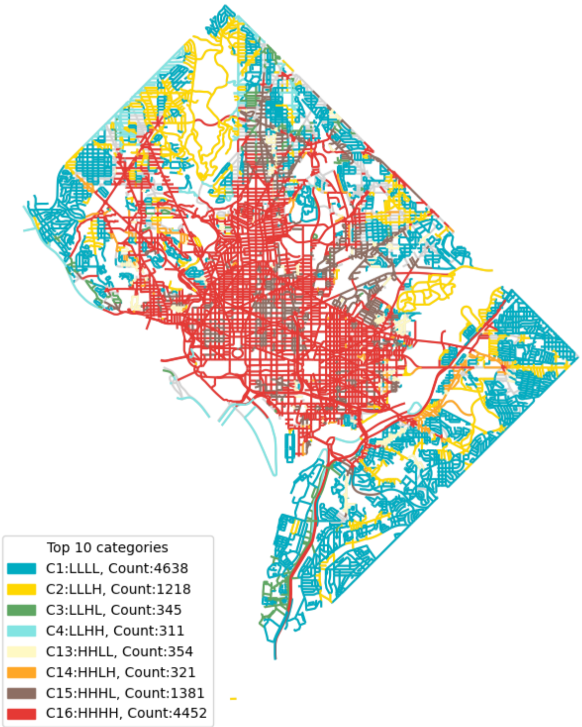
(c) Weekend Afternoon (WE3)



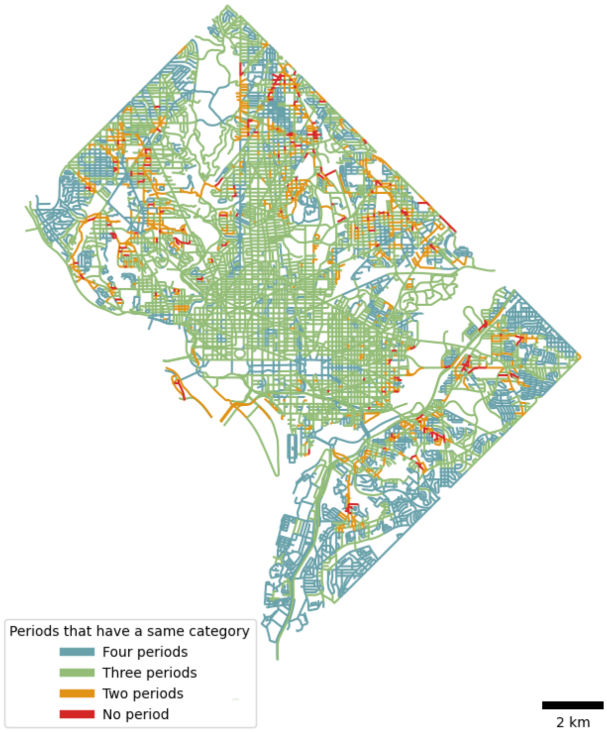
(d) Weekday Afternoon (WD3)

Figure 6. Mobility Vitality, a measure combining four transit modes at four individual periods. This illustrates the spatial distribution of the varying popularity of these four modes across different periods. In the legend, each type is followed by the combination of the four modes (in the order of LS, LB, CB, ST, where 'L' indicates low and 'H' indicates high) and the total count of road segments in that category. For clarity, only the top 10 categories for each specific period are labeled. Road segments belonging to the bottom six categories are shown in gray to avoid excessive clutter and ensure the map remains legible.

modes are primarily located in the densely gridded residential areas on the outskirts of the city. Fig. 7a shows the most prominent categories of MV across all mobility modes. As expected, parks and riverside trails consistently show high volumes only for ST, indicating that these routes are primarily chosen for recreational running rather



(a) Mobility Vitality
(Most prominent categories)



(b) Mobility Vitality
(Similarity over time)

Figure 7. Combination and comparison of Mobility Vitality across various time periods. Fig. 7a shows the spatial distribution of our four mobility modes. Notably, for clarity and simplicity, only the 10 most prominent categories out of the total 16 are presented. Fig. 7b illustrates how many time periods among the four in Fig. 6 share the same category for each road segment.

than for shared biking or e-scooters. However, Military Rd NW in Rock Creek Park and Anacostia Fwy alongside the Anacostia River remain popular across all four modes. And both roads are classified as principal arterial roads in D.C.

When examining how much the category of each road segment changes across these four representative periods, we found that the roads mentioned above mostly belong to the same category throughout a typical week (blue and green roads in Fig. 7b). This indicates that people's likelihood or willingness to choose these biking or running routes remains relatively constant over time. Blue represents roads that belong to the same category across all four periods. When compared to the yearly volume map on the left, we can see that these roads are at the two extremes of traffic flow: they are either in the most suburban, low-traffic areas or in the busiest central areas like the National Mall and 16th St NW. The roads marked in green, which have the same category across three periods, are mostly concentrated in the middle of the city. The difference for these roads primarily occurs in WD4, where the volume shifts from high across all four modes to high only for the three biking modes, while running volume drops to low.

Unlike the blue and green categories, which tend to cluster together in different areas, the red and orange roads almost always appear together but are scattered throughout the suburban areas surrounding the city center. They are not connected but rather dispersed across various locations (Fig. 7b). Compared to the left figure, these roads do not share common traffic volume characteristics—some belong to high-volume categories, others to low-volume categories, and some are even gray in the left figure, indicating that they belong to categories with very few counts, making them "distinctive" roads. Despite their differences in traffic volume across the four modes, these roads consistently appear where main roads intersect with side roads, where large and small blocks meet, and at the boundaries between blocks with different functions, such as parks, residential areas, and university campuses.

6 Discussion

This study introduces MV, a novel measure that captures dynamic interactions through active and micro-mobility modes, providing an in-depth understanding of urban planning and policy-making. Looking at the analysis of Washington, D.C., for instance, biking and scooter activity is very focused downtown, whereas running routes seem to be more spread out in parks and along riverwalks. This is indicative of certain infrastructure investments, such as a need for increased bike lanes downtown and increased recreational spaces in peripheral areas.

MV also reveals time-of-day differences in transportation mode usage: for example, in D.C., biking usage for commuting is much higher during rush hours, while evening usage is more varied. This points to the development of plans and policies that could target projects specific to certain times, such as dynamic lane allocations or adjustments in bike-sharing systems depending on peak/off-peak hours. Furthermore, our analysis shows that shared micromobility patterns fluctuate more significantly within a single day than between matching time periods on weekdays and weekends. This implies that dynamic policymaking should focus on real-time, intra-day adaptations rather than relying on separate policies for weekdays versus weekends.

From a policy perspective, MV helps identify underserved areas for infrastructure improvements and prioritize high-volume, high-similarity, and high-MV roads for maintenance. Furthermore, suggest interventions to increase accessibility in low-MV areas. More importantly, visualizing traffic across different modes helps urban planners optimize transport networks, improve safety, and implement human-oriented design.

Limitation and Future Work

This study has a few limitations that future work can address. First, for simplicity, we used the median to divide each mode's volume into high and low categories, but more granular divisions could be more informative. And when combining the four mobility modes into a single Mobility Vitality measure, we treat each mode equally. This is a quick and straightforward approach. However, in practical transportation planning, it is essential to assign different weights based on expert recommendations and specific optimization goals. Second, our study only presented road usage patterns using aggregated eight-weekly time series. This preliminary analysis serves as a foundational framework that can be extended to various temporal granularities to uncover more nuanced insights into traffic dynamics. For example, by segmenting data into hourly intervals, where each hour represents a separate time series with 60 minutes as timestamps, we can identify the most distinctive hours of the day in terms of road usage. This finer granularity allows for the detection of specific patterns, such as peak congestion periods or quieter off-peak times, facilitating more precise traffic management strategies. Future research could build upon this framework by incorporating real-time traffic data, enabling a more detailed and dynamic understanding of traffic flow. Third, expanding mobility types to include modes like taxis, buses, and light rail could further enhance the analysis.

Another limitation is the underrepresentation of certain population groups. First, the bike-sharing and shared e-scooter datasets used in our analysis do not fully represent overall biking and e-scootering patterns in the city, as they exclude personal biking and privately-owned e-scooter trips. Similarly, the Strava dataset primarily captures activities of more athletic and ambitious runners, which likely introduces bias by overlooking casual or less active runners. Additionally, pedestrian activity, which constitutes an essential component of active mobility and significantly contributes to vitality, was not included in this study. Therefore, incorporating broader datasets—such as personal device tracking, pedestrian flow data, and surveys—could provide a more comprehensive picture of mobility vitality in future research.

7 Conclusion

This study advances the understanding of urban vitality by introducing the concept of *mobility vitality*, which captures dynamic moving activities, in this case through the lens of active and micro-mobility modes. We quantified both spatial and temporal variability among four different modes of mobility, namely dockless Lime scooters, dockless Lime bikes, docked Capital Bikeshare, and Strava running activities. Furthermore, we use a spatiotemporal alignment approach to assess similarities and differences between modes and across regions, allowing us to generate a measure of mobility vitality for each region of the city. This will offer a new, holistic approach for urban planners and policymakers to find high-usage regions across different modes of mobility. The approach will enable the understanding of the underlying mechanism of active and micro-mobility with a view to enhancing efficiency in urban transport networks. Understanding and leveraging dynamic patterns of human movement will allow us to build more vibrant, livable, and sustainable cities.

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References

Chen, S., Lang, W., and Li, X.: Evaluating Urban Vitality Based on Geospatial Big Data in Xiamen Island, China, Sage Open, 12, 21582440221134 519, https://doi.org/10.1177/21582440221134519, 2022.

Cuturi, M.: Sinkhorn distances: Lightspeed computation of optimal transport, Advances in neural information processing systems, 26, 2013.

Dong, Q., Cai, J., Chen, S., He, P., and Chen, X.: Spatiotemporal analysis of urban green spatial vitality and the corresponding influencing factors: A case study of Chengdu, China, Land, 11, 1820, 2022.

Gehl, J.: Life Between Buildings, vol. 23, Van Nostrand Reinhold, New York, 1987.

Gonzalez, M. C., Hidalgo, C. A., and Barabasi, A.-L.: Understanding individual human mobility patterns, nature, 453, 779–782, 2008.

Haklay, M.: How good is volunteered geographical information? A comparative study of OpenStreetMap and Ordnance Survey datasets, Environment and planning B: Planning and design, 37, 682–703, 2010.

Jacobs, J.: The Death and Life of Great American Cities, Random House, 1961.

Janati, H., Cuturi, M., and Gramfort, A.: Spatio-Temporal Alignments: Optimal transport through space and time, https://arxiv.org/abs/1910.03860, 2019.

Kang, C., Fan, D., and Jiao, H.: Validating activity, time, and space diversity as essential components of urban vitality, Environment and Planning B: Urban Analytics and City Science, 48, 1180–1197, https://doi.org/10.1177/2399808320919771, 2021.

Kantorovich, L. V.: Mathematical methods of organizing and planning production, Management science, 6, 366–422, 1960.

Lai, Y., Li, J., Zhang, J., Yan, L., and Liu, Y.: Do Vibrant Places Promote Active Living? Analyzing Local Vibrancy, Running Activity, and Real Estate Prices in Beijing, International Journal of Environmental Research and Public Health, 19, 16 382, 2022.

Li, Q., Cui, C., Liu, F., Wu, Q., Run, Y., and Han, Z.: Multidimensional Urban Vitality on Streets: Spatial Patterns and Influence Factor Identification Using Multisource Urban Data, ISPRS International Journal of Geo-Information, 11, https://doi.org/10.3390/ijgi11010002, 2022a.

Li, S., Wu, C., Lin, Y., Li, Z., and Du, Q.: Urban morphology promotes urban vibrancy from the spatiotemporal and synergetic perspectives: A case study using multisource data in Shenzhen, China, Sustainability, 12, 4829, 2020.

Li, X., Li, Y., Jia, T., Zhou, L., and Hijazi, I. H.: The six dimensions of built environment on urban vitality: Fusion evidence from multi-source data, Cities, 121, 103 482, 2022b.

Liu, D. and Shi, Y.: The Influence Mechanism of Urban Spatial Structure on Urban Vitality Based on Geographic Big Data: A Case Study in Downtown Shanghai, Buildings, 12, https://doi.org/10.3390/buildings12050569, 2022.

Liu, X., Song, Y., Wu, K., Wang, J., Li, D., and Long, Y.: Understanding urban China with open data, Cities, 47, 53–61, 2015.

Lu, Y., Xiao, Y., and Ye, Y.: Urban density, diversity and design: Is more always better for walking? A study from Hong Kong, Preventive medicine, 103, S99–S103, 2017.

Lynch, K.: Good City Form, MIT Press, 1984.

McKenzie, G.: Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C., Journal of Transport Geography, 78, 19–28, https://doi.org/https://doi.org/10.1016/j.jtrangeo.2019.05.007, 2019.

Montgomery, J.: Editorial urban vitality and the culture of cities, 1995.

Nieuwenhuijsen, M. J.: Urban and transport planning pathways to carbon neutral, liveable and healthy cities; A review of the current evidence, Environment international, 140, 105 661, 2020.

Nocerino, R., Colorni, A., Lia, F., and Luè, A.: E-bikes and E-scooters for smart logistics: environmental and economic sustainability in pro-E-bike Italian pilots, Transportation research procedia, 14, 2362–2371, 2016.

Qiang, D. and McKenzie, G.: Mobility Vitality: Assessing Neighborhood Similarity Through Transportation Patterns In New York City, in: 12th International Conference on Geographic Information Science (GIScience 2023), edited by Beecham, R., Long, J. A., Smith, D., Zhao, Q., and Wise, S., vol. 277 of *Leibniz International Proceedings in Informatics (LIPIcs)*, pp. 61:1–61:6, Schloss Dagstuhl – Leibniz-Zentrum für Informatik, Dagstuhl, Germany, https://doi.org/10.4230/LIPIcs.GIScience.2023.61, 2023.

Qiu, C., Cheng, J., Lu, Y., and Zhang, T.: Estimating exercisality on urban trails using physical exercise trajectory data and network-constrained approach, Social Science Medicine, 361, 117 361, https://doi.org/https://doi.org/10.1016/j.socscimed.2024.117361, 2024.

Sulis, P., Manley, E., Zhong, C., and Batty, M.: Using mobility data as proxy for measuring urban vitality, 16, 137–162, 2018.

Sung, H. and Lee, S.: Residential built environment and walking activity: Empirical evidence of Jane Jacobs' urban vitality, Transportation Research Part D: Transport and Environment, 41, 318–329, 2015.

Tu, W., Zhu, T., Zhong, C., Zhang, X., Xu, Y., and Li, Q.: Exploring metro vibrancy and its relationship with built environment: a cross-city comparison using multi-source urban data, Geo-spatial Information Science, 25, 182–196, https://doi.org/10.1080/10095020.2021.1996212, 2022.

Wu, C., Ye, X., Ren, F., and Du, Q.: Check-in behaviour and spatio-temporal vibrancy: An exploratory analysis in Shenzhen, China, Cities, 77, 104–116, 2018.

Wu, W. and Niu, X.: Influence of built environment on urban vitality: Case study of Shanghai using mobile phone location data, Journal of Urban Planning and Development, 145, 04019 007, 2019.

Xia, C., Yeh, A. G.-O., and Zhang, A.: Analyzing spatial relationships between urban land use intensity and urban vitality at street block level: A case study of five Chinese megacities, Landscape and Urban Planning, 193, 103 669, 2020.

Yang, L., Mingbo, W., Chen, Y., and Wu, C.: Examining the impact of the urban transportation system on tangible and intangible vitality at the city-block scale in Nanjing, China, Environment and Planning B: Urban Analytics and City Science, https://doi.org/10.1177/23998083231223867, 2023.

Ye, Y., Li, D., and Liu, X.: How block density and typology affect urban vitality: An exploratory analysis in Shenzhen, China, Urban Geography, 39, 631–652, 2018.

Yue, H. and Zhu, X.: Exploring the relationship between urban vitality and street centrality based on social network review data in Wuhan, China, Sustainability, 11, 4356, 2019.

Yue, W., Chen, Y., Thy, P. T. M., Fan, P., Liu, Y., and Zhang, W.: Identifying urban vitality in metropolitan areas of developing countries from a comparative perspective: Ho Chi Minh City versus Shanghai, Sustainable Cities and Society, 65, 102 609, https://doi.org/https://doi.org/10.1016/j.scs.2020.102609, 2021.

Zeng, C., Song, Y., He, Q., and Shen, F.: Spatially explicit assessment on urban vitality: Case studies in Chicago and Wuhan, Sustainable cities and society, 40, 296–306, 2018.

Zeng, P., Wei, M., and Liu, X.: Investigating the Spatiotemporal Dynamics of Urban Vitality Using Bicycle-Sharing Data, Sustainability, 12, https://doi.org/10.3390/su12051714, 2020.

Zhang, B., Chen, S., Ma, Y., Li, T., and Tang, K.: Analysis on spatiotemporal urban mobility based on online car-hailing data, Journal of Transport Geography, 82, 102 568, https://doi.org/https://doi.org/10.1016/j.jtrangeo.2019.102568, 2020.

Zhang, J., Liu, X., Tan, X., Jia, T., Senousi, A. M., Huang, J., Yin, L., and Zhang, F.: Nighttime vitality and its relationship to urban diversity: an exploratory analysis in Shenzhen, China, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 15, 309–322, 2021.

Zhang, Z., Zhang, Y., He, T., and Xiao, R.: Urban Vitality and its Influencing Factors: Comparative Analysis Based on Taxi Trajectory Data, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 15, 5102–5114, https://doi.org/10.1109/JSTARS.2022.3183176, 2022.

Zhu, J., Li, B., Ouyang, H., Wang, Y., and Bai, Z.: Understanding Urban Residents' Walking Exercise Preferences: An Empirical Study Using Street View Images and Trajectory Data, Buildings, 14, 549, 2024.