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The travel pattern difference in dockless micro-mobility: Shared e-bikes versus shared bikes

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ABSTRACT

To facilitate the tailoring of dockless bike-sharing and electric bike (e-bike) sharing services and assist in formulating effective regulations, this study aims to unravel the spatio-temporal travel patterns specific to e-bike-sharing and bike-sharing systems, utilising interpretable machine learning methods and a large-scale trip-level dataset in Kunming, China. The results show that shared bikes and e-bikes exhibit overall similarities and subtle differences in many aspects, such as trip attributes and spatial distribution. Additionally, both shared bikes and shared e-bikes have three basic temporal patterns for commuting and recreational purposes. Regarding the differences, e-bike sharing networks are more dispersed and bigger, and bike sharing tends to form densely connected clusters of flow, exhibiting a local concentration of activity. Besides, the commuting activities within e-bike sharing systems exhibit two patterns: direct travel to the destination and integration with public transit. In contrast, shared bikes predominantly rely on public transit transfers for commuting purposes.

1. Introduction

Micro-mobility possesses the potential to serve a wide range of travel purposes for distances under 8 km, accounting for approximately 50 to 60 per cent of total trips in China, the European Union, and the United States (McKinsey, 2019). Recently, the integration of emerging e-bikes into bike-sharing programs has introduced new dimensions to shared micro-mobility and enhanced sustainable transportation options by providing an enhanced cycling experience with the assistance of electric power. Improving the overall convenience and accessibility of bike-sharing systems, shared e-bikes can save physical effort, broaden cycling to a wider range of territories and trips (Marincek, 2023), and decrease carbon emissions (Li et al., 2023). Some scholars pointed out the feasibility of the e-bike city, and proposed to further promote the benefits brought by e-bikes to cities (Ballo et al., 2023).

However, the widespread adoption of shared e-bikes also presents new challenges. The high production cost, charging demand, and operation and maintenance cost lead to a higher need for matching between supply and demand. Meanwhile, the increased risks associated with higher speeds of e-bikes, especially when mixed with shared bikes (Ma et al., 2019), necessitate enhanced regulation and meticulous deployment. Besides, excessive investment in shared e-bikes potentially negatively impacts other public transportation trips since the introduction of shared e-bikes not only reduces car trips but also can reduce the use of shared bikes and public transit such as buses and subways (Li et al., 2023). Due to the differences between bike and e-bike sharing modes, spatio-temporal preferences

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for their use may also vary. Understanding the differences in spatio-temporal travel patterns inside shared micro-mobility is crucial for effectively designing, optimising, and planning different systems, allowing for the customisation of different shared micro-mobility services to better meet user needs and improve riding safety. The comparative analysis helps reveal the unique characteristics, advantages, limitations, and specific use cases associated with each mode, providing a comprehensive understanding of their respective impacts. It guides infrastructure development, including the establishment of bike lanes and parking facilities, the allocation of charging infrastructures, and the division of operation coverage (Meng et al., 2023) for conventional bike-sharing and e-bike-sharing programs. Furthermore, identifying these differences can aid in better matching supply with demand and reducing costs.

Therefore, there is an emerging number of studies focusing on the comparison between shared e-bikes and shared bikes in recent years. Most of these studies relied on questionnaires and assumptions to explore the factors influencing travel from the subjective perspective of interviewees (Campbell et al., 2016) and the differences in riding experiences of e-bikes and bicycles (Ling et al., 2017). However, the results may be affected by the subjectivity and memory bias of survey questionnaires and sample selection.

Leveraging extensive, real trip-level data offers opportunities to address the limitations of prior survey-based research and further explore the differences in actual riding behaviour and their spatial–temporal patterns. Based on large-scale trip-level data, existing research compares the differences in basic travel time and distance of dockless bike sharing and e-bike sharing (Ye et al., 2021), the operational differences between docked and dockless micro-mobility modes among docked e-bikes, docked bikes, dockless e-scooters, and dockless e-bikes (Reck et al., 2021), and highlights the differences in the use of docked bikes, docked e-bikes, and dockless e-bikes before and after the COVID-19 pandemic (Li et al., 2021). Nevertheless, to the best of our knowledge, the differences in spatial–temporal travel patterns between shared bikes and e-bikes in dockless conditions are not investigated. Previous studies underscored the more flexible choice for users in dockless bike sharing mode than in docked one. The comparative study on the spatio-temporal travel pattern between dockless e-bikes and bikes could better reflect users' inherent spatial preferences and give a direct reference for the operation of dockless micro-mobility systems than studies based on docked systems.

To address this need, this study obtained large-scale datasets from dockless bike-sharing and e-bike-sharing programs to investigate and compare the spatio-temporal travel patterns of bike-sharing and e-bike-sharing systems, in terms of four aspects, including trip attributes, flow network structures, basic temporal patterns, and relationships with different land use functions and their changes over time. Compared with previous studies focused on the difference between docked and dockless micro-mobility systems, this study concentrates on the spatio-temporal differences in cycling patterns between human-powered and electric-assisted rides under the same dockless micro-mobility scenario. Kunming was selected as the study case due to both shared e-bikes and shared bikes operating within the same operational space, which enables a straightforward comparison of travel behaviours under consistent spatio-temporal conditions. Understanding the similarities and differences between these modes can help guide the expansion, integration, and management of these systems in urban environments, ultimately contributing to the development of sustainable and efficient transportation networks.

The remainder of the paper is structured as follows. Section 2 provides a review of the literature. Section 3 introduces the study area and dataset, establishing the foundation for the analysis. In Section 4, the study describes the fundamental frameworks utilised for travel pattern analysis, including flow structure analysis, non-negative matrix factorisation method, and elasticity analysis. Section 5 presents the findings encompassing basic trip attributes, spatial flow network structure, decomposed temporal patterns, and the correlation between ridership and land use functions. Finally, the paper concludes by summarising key findings, policy implications, limitations, and offering suggestions for future research in the last section.

2. Literature review

2.1. Comparative analysis in various micro-mobility modes

The booming of shared micro-mobility is regarded as a potential contributor to the behaviour change of car-dependent lifestyles and the reduction of traffic congestion, air pollution and health challenges (Cao & Shen, 2019; Cerutti et al., 2019; McQueen et al., 2019). Bike sharing, as an earlier form of shared micro-mobility system, has developed for more than half a century (Wang & Sun, 2022). From the first bike-sharing system in Amsterdam (DeMaio, 2009; Ploeger & Oldenziel, 2020) to the emergence of e-bike sharing on the streets around the world (Galatoulas et al., 2020), the development of shared micro-mobility has made it more convenient and sustainable for human mobility and activities.

In this context, shared micro-mobility, ranging from docked and dockless bike sharing to e-bike and e-scooter sharing, has received considerable attention from scholars in transportation and urban planning (Campbell et al., 2016). Although most quantitative studies attempted to reveal travel behaviour and spatio-temporal patterns of shared micro-mobility from one specific shared mode (Abduljabbar et al., 2021), some comparative studies are also on the rise. Some studies focused on the comparison between shared and private micro-mobility in terms of bikes, e-bikes, and e-scooters (Reck et al., 2022). Some studies paid more attention to the differences between docked and dockless operations (Reck et al., 2021; Ma et al., 2020). Moreover, the different travel behaviours among different shared vehicles have also gained great interest. For example, Li et al. (2021) contrasted the use and travel behaviour of various shared vehicles (i.e., docked bikes, docked e-bikes, dockless e-scooters, and dockless e-bikes) before and after the onset of the pandemic. McKenzie (2020) distincted use patterns, peak use times, and preferred locations of bike-sharing, car-sharing, and e-scooter sharing. However, the field of micro-mobility lacks direct comparative analyses of the spatio-temporal distribution patterns between dockless shared bikes and dockless shared e-bikes. Considering the differing operational modes, dockless shared micro-mobility offers a more accurate reflection of users' actual travel habits and spatial preferences. Consequently, comparative studies on shared bikes and e-bikes are essential to discern the distinct preferences for physical activity-based micro-mobility versus electronically-powered options.

Therefore, our subsequent sections will concentrate on examining the riding behaviour and spatial patterns of bike sharing and e-bike sharing, highlighting their distinct characteristics.

2.2. The use characteristics of shared bike and e-bike systems

The state-of-art research investigated and compared the spatio-temporal characteristics of the use of shared bikes and e-bikes. Studies based on docked and dockless bike-sharing data have shown morning and evening peaks on weekdays (Chen et al., 2020; O`Brien et al., 2014) and no distinct commuting peak (Zhang et al., 2021) or less prominent one on weekends (Chen et al., 2020), implying the prominent role of bike sharing in substituting or complementing commuting trips. Regarding riding duration and distance, studies revealed less than 30-minute riding durations of bike sharing (Shen et al., 2018) and reported that the typical travel distance for docked bike-sharing falls within the range of 1 km to 5 km (Kou & Cai, 2019; Zhao et al., 2015), while the shared dockless bike-sharing trips are typically less than 2 km (Shen et al., 2018). The trips made in dockless bike-sharing systems exhibit better coverage compared to docked bike-sharing due to the absence of station constraints (Chen et al., 2020), but also tend to be concentrated in the central areas of cities, with use gradually decreasing as one moves away from these central regions (Zheng et al., 2022).

Since shared e-bikes combine the merits of shared bikes and electric vehicles (Winslott Hiselius & Svensson, 2017), studies on e-bike sharing indicate that users riding e-bikes can travel at higher speeds with less physical effort, travel for longer distances, and climb slopes easily than bikes (Allemann & Raubal, 2015; Langford, 2013; Popovich et al., 2014). Empirical studies revealed that the average daily distances covered on e-bike sharing systems varied from 2 km to 10 km (Bourne et al., 2020), which varies depending on the purpose of the trip. According to Haustein and Møller (2016), recreational riders covered greater distances per trip than those who used e-bikes for utilitarian purposes such as commuting, shopping, or running errands. Additionally, Winslott Hiselius and Svensson (2017) found that e-bikes were primarily used for commuting, averaging 3.6 days per week, while leisure purposes accounted for 1.4 days per week. Moreover, a survey comparing bike sharing and e-bike sharing choices underlined that e-bike sharing is less dependent on trip distance, high temperatures, and poor air but shows significant differences among user demographics(Campbell et al., 2016), which is also consistent with a study that suggested that younger adults tend to cycle longer distances than older adults and e-bike use decreases as age increases (Kroesen, 2017). However, numerous studies also paid attention to the e-bike riding risks and safety issues, revealing that the primary hazardous riding behaviours observed with e-bikes include unauthorised use of motor vehicle lanes, excessive speeding, running red lights, and unlawful riding against traffic flow or in reverse (Ma et al., 2019), and showcasing that the perceived e-bike safety is associated with the use frequency (Gogola, 2018), winter e-bike use and cycling for diverse trips (Marincek, 2023). Therefore, the accurate arrangement and regulation of shared e-bikes, considering the varying spatio-temporal use preferences between shared bikes and e-bikes, hold significant importance. Nevertheless, despite some studies shedding light on the differences in bike and e-bike sharing choices (Ye et al., 2021), their overall user demographics, temporal dynamics of trips, and trip features are still unclear.

2.3. The spatial patterns and relationship with land use and public transportation for shared bike and e-bike uses

Bike sharing and e-bike sharing, as new modes of transportation, can change individuals' travel behaviours. Therefore, numerous studies investigated the relationship between bike or e-bike sharing with land use and public transit to infer the travel demand and explore the substitution or complementation role of shared bikes and e-bikes in public transportation and private vehicles. Research on bike-sharing shows that approximately 44 % of dockless bike-sharing activities occur within a 500-meter radius of metro stations, contributing to improved accessibility to public transportation and congestion alleviation (Global and Planning, 2017; Fan & Zheng, 2020). Some recent studies focus on investigating the spatial structure of bike-sharing by applying the complex network science method. An increasing number of studies are analysing the flow characteristics of transportation systems by dividing them into geographic units (Li et al., 2021; Xie et al., 2021; Yildirimoglu & Kim, 2018). Austwick et al. (2013) utilised node centrality and community detection algorithms to compare docked bike-sharing systems in five cities. Lin et al. (2020) employed community detection algorithms in complex networks to divide Beijing into 120 sub-regions, revealing a polycentric distribution pattern in travel demands for dockless bike-sharing. Similarly, Li & Xu (2022) quantified changes in the dockless bike-sharing network structure before and after the COVID-19 pandemic using network analysis techniques, revealing a decentralised trend in the bike-sharing flow structure.

Unlike bike sharing, which mainly aims to resolve the last-mile connectivity problem and is used for recreation and exercise (Hiselius and Svensson, 2017; Ling et al., 2017), e-bike sharing plays a more critical role as a utilitarian transport mode (Ling et al., 2017; Lobben et al., 2018; Sundfør & Fyhri, 2017), resulting in the potential to become an alternative to short- and medium-distance car trips (Haustein & Møller, 2016; Ioakimidis et al., 2016; Moser et al., 2018). Numerous survey-based studies suggested that e-bikes can be used for various purposes, including commuting, shopping, running errands, and recreation (He et al., 2019; Langford, 2013; Munkácsy & Monzón, 2017). In addition, according to Choi et al. (2023), users of e-bike sharing exhibited a reasonably consistent travel pattern even during the COVID-19 pandemic, which also suggests that shared e-bikes have the potential to be widely adopted as a future urban transportation solution. Nevertheless, empirical studies also have underscored that while e-bike trips may serve as substitutes for car travel (Söderberg et al., 2021), they predominantly displace conventional bike trips and, to a lesser extent, public transit use (Kroesen, 2017; Li et al., 2023). This implies that the overuse of shared e-bikes might counterproductively impede efforts to foster sustainable and safe public transportation systems. In this condition, a judicious approach is warranted in the allocation and implementation of shared e-bike initiatives. However, the lack of e-bike trip data leads to insufficient research on sharing e-bikes in terms of the spatio-temporal patterns and the relationship of e-bike trips with land use and public transportation. Only one study used e-bike sharing data to explore spatio-temporal patterns and figured out its significant association with commercial public transit stations and hotel density (Ye et al., 2021). Nevertheless, the direct differences in spatio-temporal characteristics rather than the travel behaviour between bike and e-bike sharing are still under-answered.

2.4. Summary

Overall, previous research exhibits two primary limitations. Firstly, there is a scarcity of research investigating the travel patterns of dockless shared e-bikes, particularly in terms of flow network structure, underlying temporal patterns, and the spatio-temporal relationship between travel demand and land functions. Secondly, there is a lack of comparative empirical research based on large-scale actual travel data that examines the travel patterns of dockless e-bike sharing and dockless bike sharing in the same spatio-temporal contexts.

3. Data and study area

This research takes the main urban area of Kunming as the study area (Fig. 1), focusing on analysing the travel patterns of both bike-sharing and e-bike-sharing systems. Situated in the southwestern part of the country and nestled within a basin surrounded by mountains, Kunming is the capital city of Yunnan province in China and is a vibrant and rapidly developing urban centre known for its

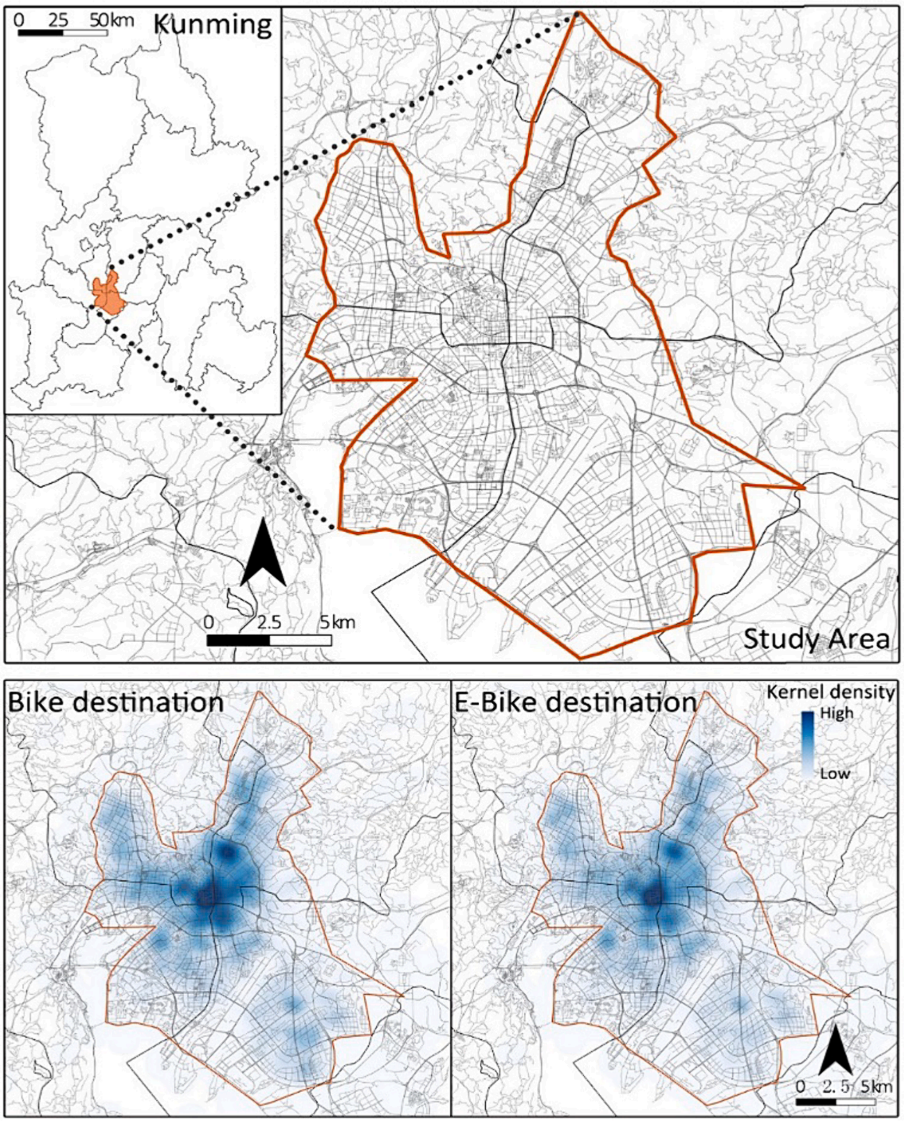

Fig. 1. Study area and visualisation of destination data for bike sharing and e-bike sharing.

pleasant year-round climate and rich cultural heritage. The population in the main urban area of Kunming is 4.7 million.

Regarding conventional shared bikes, the government encouraged their launch in both large and medium-sized Chinese cities, while shared e-bikes are primarily permitted for operation in smaller cities and counties. However, Kunming stands out as one of the few large cities where government policies actively encouraged the utilisation of shared e-bikes. The selection of Kunming as the study case for this research is driven by the unique advantage it offers in terms of having both shared e-bikes and shared bikes available within its urban area. This availability provides an excellent opportunity to compare and analyse their respective use patterns, user preferences, and potential impacts on urban mobility. Kunming's status as a city with flourishing shared e-bike and shared bike systems allows for a comprehensive examination of the shared micro-mobility systems and their implications for sustainable transportation.

Given the availability of data, the dataset used in this study spans two weeks in March 2021, capturing approximately 2.5 million shared e-bike trips and 4 million shared bike trips (Fig. 1). The dataset is sourced from the Meituan company, including valuable information such as user attributes (user ID, gender, and age), trip attributes (start and stop time, date, and the longitude and latitude of location), and bike IDs (Table 1). The user information of the data is anonymous.

4. Methods

This study takes the 100 m*100 m grid as an analytic unit and uses the OD data of bike sharing and e-bike sharing to depict their spatio-temporal patterns via four parts (Fig. 2). First, this study provides an overview of trip attributes, including the distribution of user age, trip distance, duration, use frequency and fleets supply. Then, to reveal the differences in spatial flow network structure and identify the cycling flow cluster in selected urban areas, the clustering coefficient is used to gauge the level of spatial flow network dispersion, followed by the implementation of the Infomap cluster algorithm to identify the cycling neighbourhoods for both shared bikes and shared e-bikes. Subsequently, the non-negative matrix factorisation (NMF) method is employed to decompose temporal patterns and unveil fundamental trip purposes. Finally, elasticity analysis is utilised to explore the spatio-temporal changes in the correlations between ridership and different land uses (workplace, residential, recreation, subway station, and bus station) by controlling for socioeconomic indicators, thus illuminating the possible trip destinations in terms of urban functions throughout the day. The different steps covered by the empirical analysis are summarised in Fig. 2.

4.1. *Travel flow network structure analysis*

To compare the flow structures of bike sharing and e-bike sharing, the paper establishes cycling flow networks and identifies cycling neighbourhoods within the flow networks. The study treats cycling flow as a graph and constructs a bike-sharing trip flow network by taking origin and destination (OD) spatial units as pairs of nodes, with the trip flow between points represented as links. The higher the trip frequency between nodes, the stronger the links between them.

The paper then applies a community detection algorithm called the Infomap algorithm, which has always been used in previous flow network analyses (Li & Xu, 2022). Based on the Map equation and employing random walk and Huffman coding, the Infomap algorithm is a network clustering technique used to detect communities within networks based on the flow of information. It operates by simulating random walks on the network, using the flow of these walks to identify natural divisions between nodes. At the core of the Infomap algorithm is the Map Equation, which quantifies the description length of a random walker's movements through the network. The equation seeks to minimise this description length by optimally partitioning the network into clusters, where each cluster represents a community. The goal is to find a partition where the random walker spends a lot of time within clusters and relatively little time moving between them, thus reflecting a strong community structure. Furthermore, the Infomap algorithm utilises Huffman coding, an efficient method for data compression, to encode the paths the random walker takes. Huffman coding assigns shorter codes to frequently used paths and longer codes to less common paths. This coding scheme is integral to calculating the description length of the walker's trajectory across the network, as it directly impacts the optimisation process of the Map Equation.

The Infomap algorithm is applied to cluster the spatial units into communities. The geographic information of nodes within each community shows the spatial distribution of these communities within the city. There are stronger connections between nodes within the same community, while connections between different communities are relatively sparse. The paper defines cycling neighbourhoods as spatial communities where the spatial units are densely interlinked through bike-sharing trips, while the external links of these communities are limited.

To assess the local connectivity or clustering of nodes, the average clustering coefficient is used as an index. The average clustering coefficient is a measure that quantifies the degree to which nodes in a network tend to cluster together. It is defined as the average of the local clustering coefficients of all the nodes in the network. The local clustering coefficient for a single node measures how close its neighbours are to being a complete graph, that is, how interconnected a node's neighbours are with each other. This metric is crucial in

Table 1
Example of bike and e-bike sharing trip records.

Order id	City	Date	User id	Bike id	User gender	User age	Register date	Origin (longitude, latitude)	Destination (longitude, latitude)	Start Time	End Time
Trip No. 1	Kunming	2021–03-05	6939	7405	Male	26	2020–06-02	102.42, 25.02	102.13, 24.32	17:20	18:02

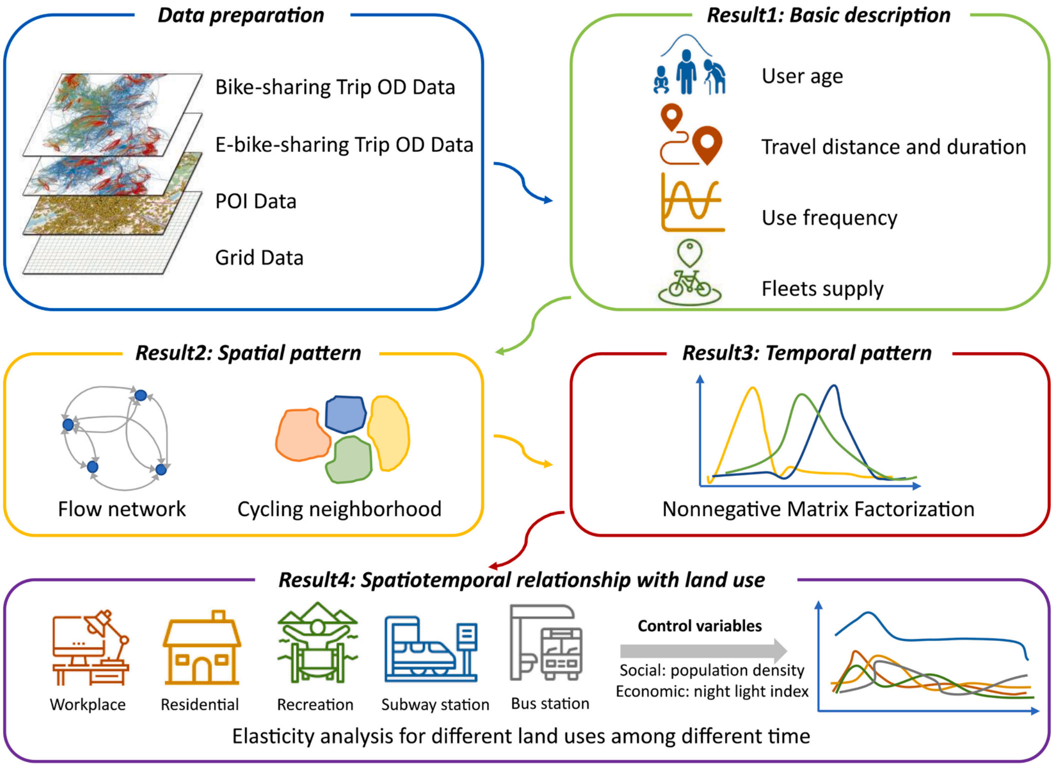

Fig. 2. Research framework.

understanding the local density of connections in a network and has been widely used to analyse the propensity for clustering within various network types (Gallotti & Barthelemy, 2015; Newman, 2003; Porta et al., 2006; Watts & Strogatz, 1998; Zhong et al., 2014). The formula for the clustering coefficient $C(v)$ of a node v is given by:

$$C(v) = \frac{2E_v}{k_v(k_v - 1)}$$

where E_v is the number of edges between the neighbours of v, and k_v is the degree of v, or the number of neighbours. The denominator $k_v(k_v - 1)$ represents the total possible number of edges between neighbours if every neighbour was connected to every other neighbour. Then, the Average Clustering Coefficient C_{avg} for the whole network is calculated as:

$$C_{avg} = \frac{1}{N}\sum\nolimits_{v \in V} C(v)$$

where N is the total number of nodes in the network, and the sum is taken over all nodes v in the network V. A higher average clustering coefficient indicates a greater level of clustering or local connectivity among the start and end locations of bike rides. The result can help improve the efficiency of vehicle scheduling and rationally design the scope of shared micro-mobility systems operation. For instance, by identifying cycling neighbourhoods (communities) with frequent internal cycling activities, fleet scheduling can be carried out within these neighbourhoods.

4.2. Non-negative matrix factorisation method

The macro travel pattern of trips can be described by some linear combinations of basis collective patterns in previous studies, such as taxi trips (Peng et al., 2012; Dong et al., 2018). Trips with the same purpose category but at different locations tend to follow similar collective time patterns for departure and arrival time based on large-scale data. For instance, even if two workplace areas are situated in different parts of a city, they should have similar time trends regarding the inflow and outflow of people. Specifically, if the number of trips between residential areas and workplaces peaks at 8:00 am (for going to work) and 5:00 pm (for returning home), this temporal trend is likely to occur in other residential areas and workplaces across the city. While the magnitude of this trend may vary in different locations, the basic temporal trend is the same. This idea can help to identify distinct basis patterns for collective flow, regardless of location, to deconstruct the random pattern of different areas. In brief, a set of basic collective patterns can be defined, with each pattern corresponding to a trip type.

NMF is a machine learning technique used for matrix factorisation. In NMF, a non-negative matrix is decomposed into two lower-rank non-negative matrices, typically referred to as the basis matrix and the coefficient matrix (Peng et al., 2012). The basis matrix represents the fundamental patterns in the data, while the coefficient matrix represents the contribution of these patterns to reconstruct the original data matrix. The goal of NMF is to find an optimal factorisation that best captures the underlying structure of the data. This is achieved by minimising a cost function, such as the Frobenius norm or Kullback-Leibler divergence, which measures the dissimilarity between the original data matrix and its reconstructed approximation. Similarly, this study applies the NMF method to e-bike sharing and bike sharing to find the basis patterns of temporal demand and intensity coefficient of the pattern for each location.

The study divides the urban area into the same-sized 100 m*100 m grids. If there are b rows and d columns in the whole urban area, we label (i,j) to represent a grid location in ith row and jth column, then $i \in [1, b] \cap \mathbb{Z}$ and $j \in [1, d] \cap \mathbb{Z}$. $\boldsymbol{h}$ is the time slot from 1 to 24 a day, and $h \in [1, 24] \cap \mathbb{Z}$. Therefore, a $1 \times h$ vector $\boldsymbol{G}_{i,j}$ is used to represent the ridership of trips along hour for location (i,j). We assume that the macro travel pattern is some linear combination of basis patterns, and these basis patterns can be decomposed from the macro pattern, so a set of $1 \times h$ vectors are defined to represent basis collective patterns with normalised numbers of trips along time h: $\boldsymbol{T}_1, \boldsymbol{T}_2, \ldots, \boldsymbol{T}_n$; **n** is the number of pattern types that we initially set up to decompose. To be more specific, the factorisation formula can be written as:

$$\begin{bmatrix} G_{1,1} \\ G_{1,2} \\ \cdots \\ G_{1,d} \\ G_{2,1} \\ G_{2,2} \\ \cdots \\ G_{b,d} \end{bmatrix} = \begin{bmatrix} S_{1,1} \\ S_{1,2} \\ \cdots \\ S_{1,d} \\ S_{2,1} \\ S_{2,2} \\ \cdots \\ S_{b,d} \end{bmatrix} \begin{bmatrix} T_1 \\ T_2 \\ \cdots \\ T_n \end{bmatrix}$$

Where $S_{b,d}$ is a set of row vectors containing different linear combinations in different locations, each of which has n coefficients. All the macro patterns $\boldsymbol{G} \in \mathbb{R}_+^{bd \times h}$ in location (i,j) can be factorised into two low-rank non-negative factors, then we could get the basis patterns $\boldsymbol{T} \in \mathbb{R}_+^{n \times h}$ and the coefficients $\boldsymbol{S} \in \mathbb{R}_+^{bd \times h}$ for each location (temporal basis pattern matrix **T**, spatial coefficients matrix **S**). Each item in **S** depicts the scale of ridership concerning the corresponding basis pattern type in location (i,j), to reflect how strong the e-bike flow of different pattern types is. It also can be abbreviated as:

$$\boldsymbol{G} = \boldsymbol{ST}.$$

4.3. The elasticity analysis

To explore the spatio-temporal change of the ridership of shared bikes and shared e-bikes to the land use function of destinations, the study conducts an elasticity analysis between different land use intensities and the trip volumes of shared e-bikes or bikes in each hour. The paper selected four typical land use function POIs, including workplaces, residential areas, recreational infrastructures, and public traffic infrastructures (subway stations and bus stops). The analysis unit is 100 m*100 m grids, and the model is established as follows:

$$lnY_{it} = \beta lnX_{it} + \gamma_i + \alpha$$

Where Y_i is the total ridership of e-bike sharing or bike sharing in grid_i at hour_t (from 7 am to 11 pm), X_i is the intensity of one land use type in grid_i, indicated by POI density, and γ_i is a set of control variables, such as population density and intensity of economic activity, represented by the night light index. The elasticity value (β) is used to indicate the sensitivity degree of each land use function to the

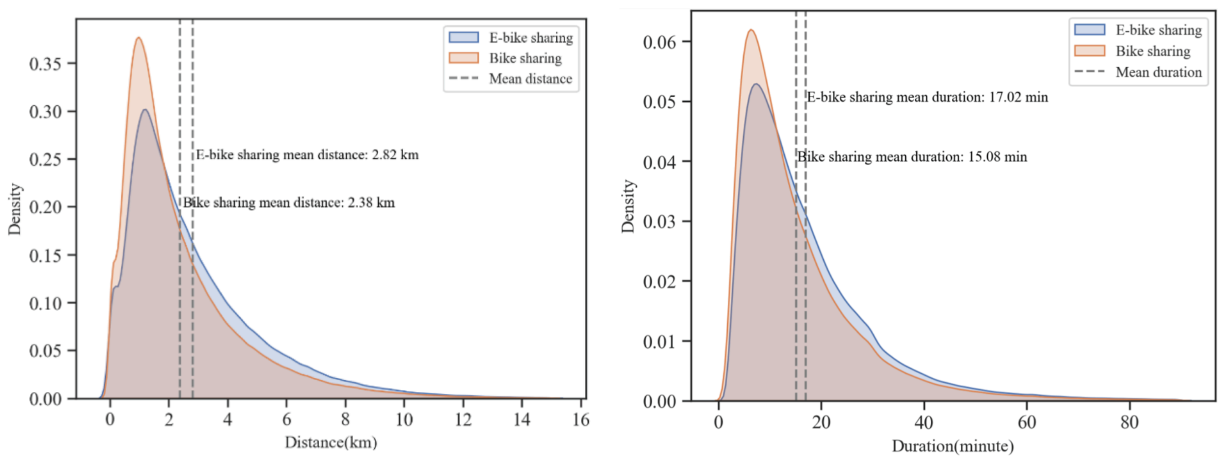

Fig. 3. Distribution of the trip distance and duration of e-bike sharing and bike sharing.

ridership, meaning that a 1 % change in X is associated with a β % change in Y. While such kind of analysis is not able to identify the causal effect of regressors on total ridership, it provides interesting exploratory insights. Elasticities are extensively employed in economic and urban planning research as dimensionless measures of effect size to assess the associations between pairs of variables (Ewing & Cervero, 2010; Li et al., 2019).

5. Result

This section aims to illustrate the travel patterns of e-bike and bike sharing, as well as their similarities and differences. It includes a basic description of trip attributes, temporal patterns, flow network structures, and the correlations between ridership and land use functions.

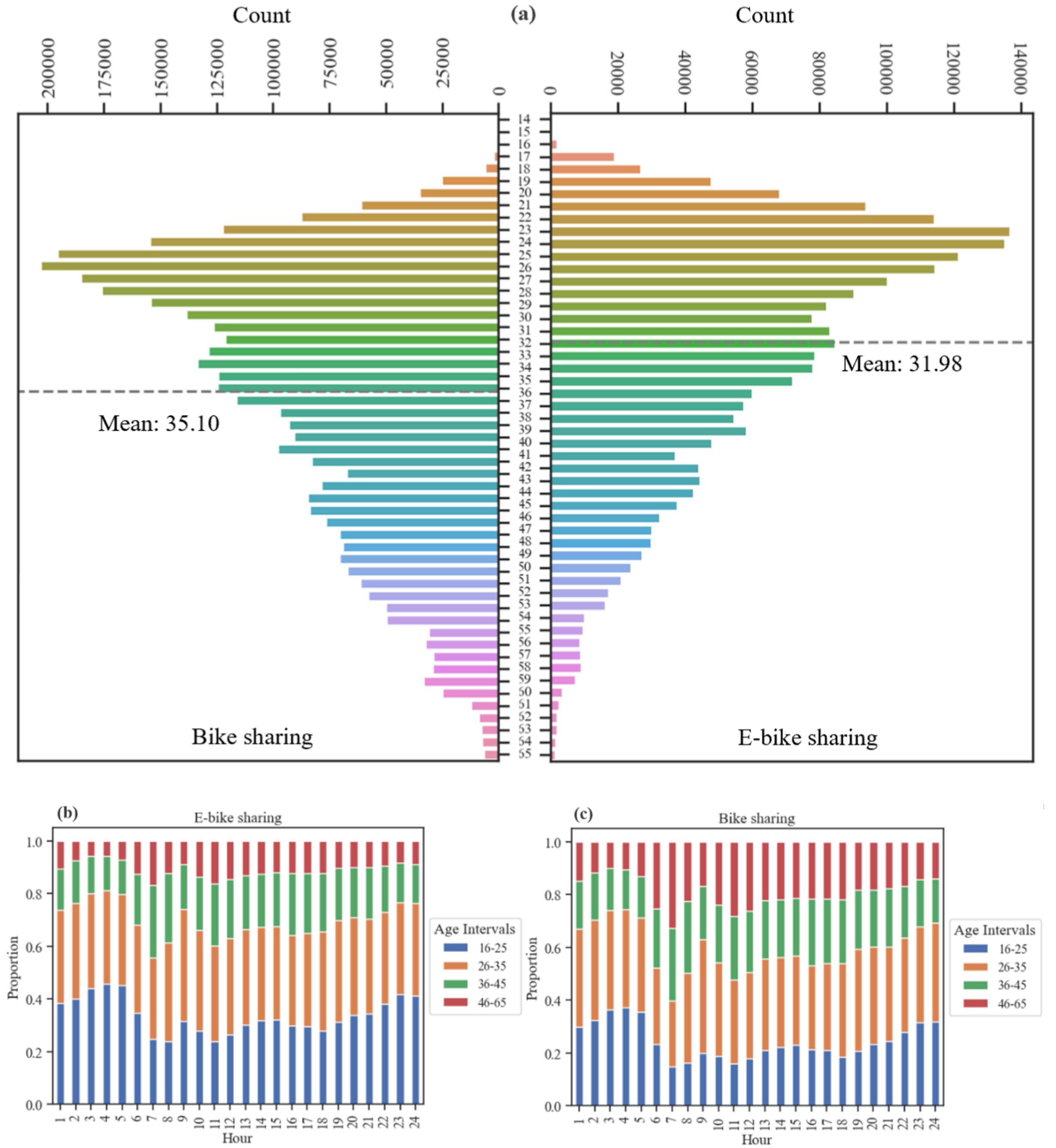

Fig. 4. The frequency distribution of age **(a)** and the distribution of users' ages throughout the day **(b, c)** for e-bike sharing and bike sharing.

5.1. Basic description

5.1.1. The travel distance and duration

Fig. 3 illustrates the overall similar distributions of trip distances and durations for e-bike sharing and bike sharing, showing that, on average, e-bike trips are about 0.5 km longer and last around 2 min longer than those of traditional bikes. The average trip distances, measured using the Manhattan Distance (Li et al., 2020), for shared e-bikes and shared bikes are 2.82 km and 2.38 km, respectively. There is not much difference in the average travel distance between weekdays and weekends. Regarding the average travel time, shared e-bikes have an average of 17.02 min, while shared bikes have an average of 15.08 min. In general, the trip distance and duration of shared e-bikes are slightly greater than those of shared bikes. This can be attributed to shared e-bikes assisting in conserving physical energy and enabling longer trips to more distant locations than shared bikes, which is consistent with previous research (Langford et al., 2013; Bikeplus, 2016). The findings also highlight the potential of shared e-bikes to substitute other short- and medium-distance transportation modes, such as cars.

5.1.2. User age

The age distribution of users in bike sharing and e-bike sharing primarily centres around the age range of 22 to 35 years (Fig. 4a), with the highest number of users occurring around 24 years old. In terms of average age, shared bike users have an average age of 35.10 years, while shared e-bike users have an average age of 31.98 years. There is a tendency for e-bike sharing to attract a younger demographic. Both bike sharing and e-bike sharing exhibit a similar age structure trend that fluctuates throughout the day (Fig. 4b, 4c). From 7 am to 7 pm, the user age tends to be higher, while from 8 pm onwards until 6 am the following day, the user age structure skews younger. The overall age structure of e-bike sharing tends to be younger than bike sharing throughout the day.

5.1.3. Use frequency

The use frequency serves as a measure of the efficiency of shared e-bike and shared bike use, reflecting fleet utilisation and turnover. It is calculated by dividing the total number of trips in one week by the total number of shared fleets. As depicted in Fig. 5, the use frequency of shared e-bikes and shared bikes is 22.18 times per week and 17.73 times per week, respectively. The vehicle utilisation rate of shared bikes is lower than that of shared e-bikes. One possible reason for this difference is that the supply of electric bicycles is lower than that of regular bicycles. Another potential reason is the convenience of shared e-bikes, which allows them to serve a broader range of people and enhance user experience, particularly when traversing uphill routes or covering long distances.

5.1.4. Fleets supply

The supply distribution of e-bike and bike fleets is usually aligned with demand patterns, primarily based on population distribution, and then adjustments to fleet size are made in response to ongoing monitoring of use data, ensuring a dynamic balance between supply and demand (Abdellaoui Alaoui & Koumetio Tekouabou, 2021).

To provide a detailed view of fleet utilisation and infer the balance between supply and demand across the urban area, the study measured the idle time of fleets by analysing the start time of each trip and the end time of the previous trip for the same bike ID. By calculating the average idle time of each bicycle before the start of each trip in each 1000*1000 m area during daytime hours, we derived the spatial distribution of the average idle times of the vehicles in these areas. Fig. 6 illustrates the deployment ratio and average idle times of shared bikes and e-bikes across different areas, highlighting how fleet distribution resembles with population density and demand indicators.

It can be observed that the average idle time before each use of a shared e-bike typically ranges from 1 to 2 h in urban areas, while

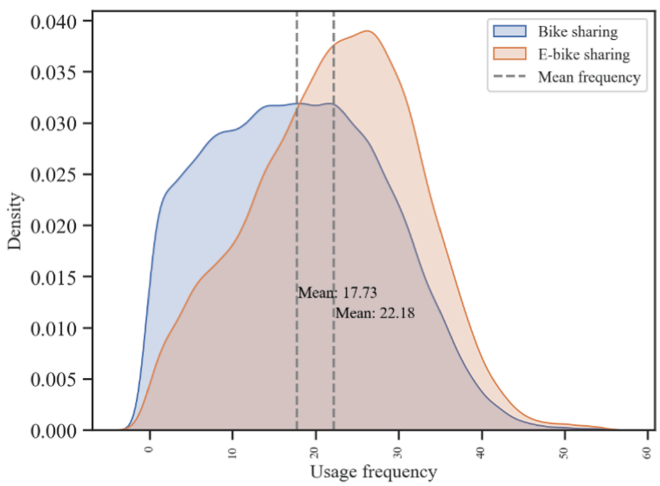

Fig. 5. Distribution of the use frequency of e-bike sharing and bike sharing.

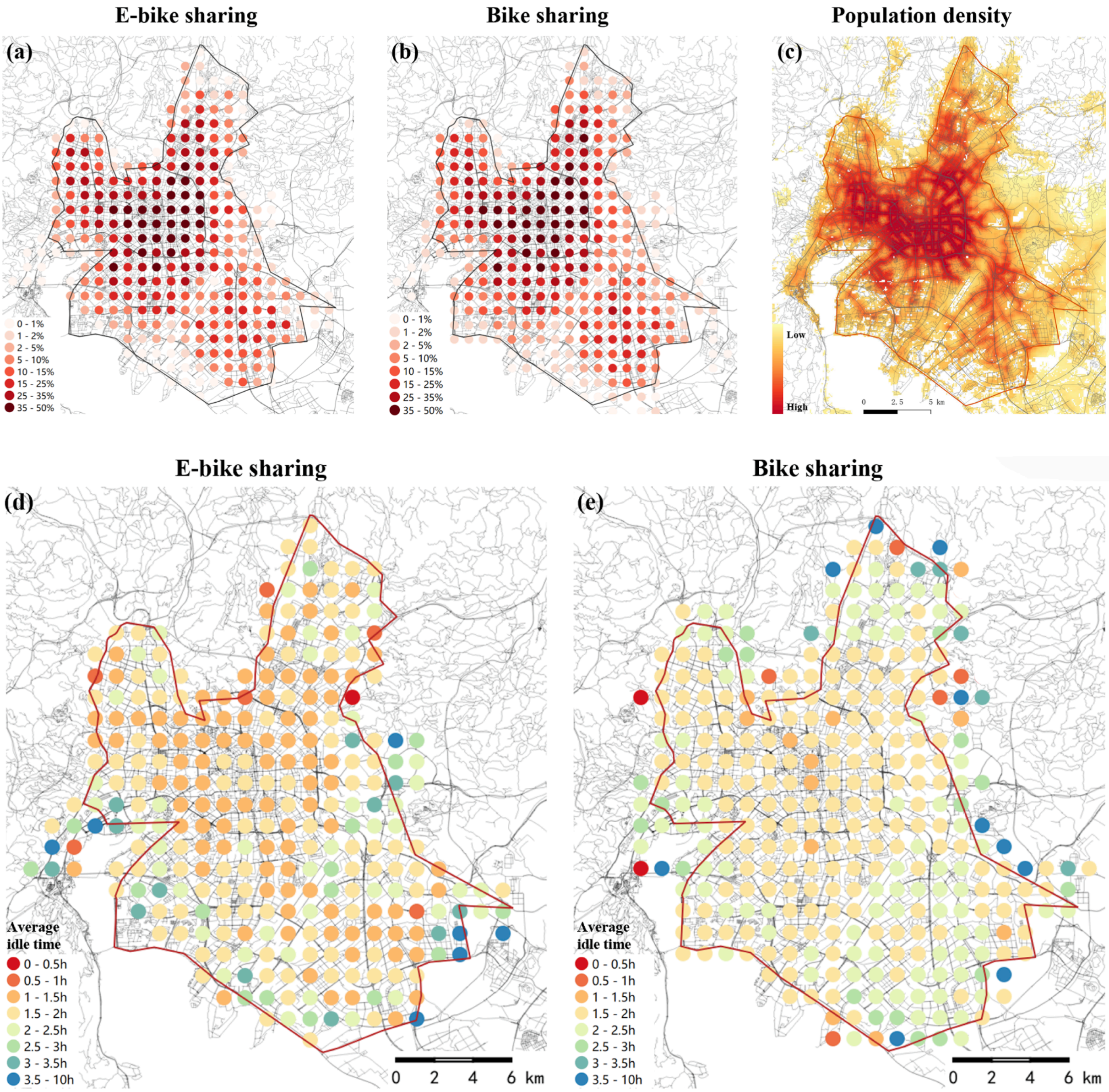

Fig. 6. The deployment ratio of vehicles **(a, b)**, the distribution of population density **(c)**, and the spatial distributions of the average idle time of e-bikes and bikes before the start of a trip **(d, e)** (Data source: https://www.worldpop.org/).

the average idle time before each trip of a shared bike is slightly longer, approximately 1.5 to 2 h (Fig. 6d, 6e), which indicates a basic balance between supply and demand for the two modes. Overall, the average idle time for each shared e-bike in the city is 1.5 h, and for shared bike fleets, it is 1.75 h. In addition, the average use rate for each shared e-bike is 0.43 times per day, and each shared bike is used, on average, 0.34 times per day. This also suggests that the supply of shared e-bikes and bikes adequately meets demand in the study area.

5.2. Spatial flow network structure

To explore the performance of shared e-bikes and shared bikes in cycling flow structures, this study established flow networks, where nodes represent the origins and destinations of trips, and edges represent the trip flows between them. Five different colours were used to represent the levels of ridership between various origins and destinations, with warmer colours indicating higher trip volume between locations. As shown in Fig. 7, Kunming exhibits a multi-centre structure with numerous commuting clusters. Some clusters have longer trip distances while others have shorter distances, which may be attributed to variations in land use structures and other community characteristics.

From the flow networks of shared bikes and e-bikes, the two modes exhibit certain similarities. In order to further explore the differences and similarities between them, this paper compares the clustering coefficients of their flow networks. The clustering coefficient is a commonly used measure in network analysis that quantifies the tendency of nodes to form clusters or communities (Gallotti & Barthelemy, 2015; Porta et al., 2006; Zhong et al., 2014). It reflects the presence and degree of community structure within a network, with a higher clustering coefficient indicating a higher degree of clustering. The average clustering coefficient of the e-bike sharing network (0.284) is lower than that of the bike sharing network (0.342), suggesting that the cycling network structure of e-bike sharing is more dispersed compared to bike sharing. Nodes in the bike-sharing network tend to form more closely connected communities. One possible reason for the lower clustering coefficient in e-bike sharing networks is the faster and more efficient mode of transportation offered by e-bikes. E-bikes can cover longer distances and travel at higher speeds compared to bikes, which means that users may have less need to cluster together in specific areas. As a result, e-bike-sharing networks may be more spread out and less likely to form tightly-knit communities.

To make the network structure clearer, the paper applied the Infomap algorithm to detect the cycling communities of shared bikes and shared e-bikes (Fig. 8). The choice of clustering algorithm parameters can also impact the results. To ensure the accuracy and reliability of the findings, the study tested different clustering level parameters of the Infomap algorithm and found that stability was achieved when the clustering level was set to 3. Subsequently, the stable clustering results were selected for comparison.

Compared to bike sharing, the community boundaries in e-bike sharing are more blurred, while the cycling neighbourhood structure in bike sharing is more apparent. Fig. 9 illustrates that e-bike sharing has relatively larger communities and fewer smaller communities compared to shared bikes, indicating that e-bike sharing expands the commuting radius of users. The distinct user characteristics and trip attributes between e-bike and bike sharing contribute to different network structures and community detection results. With electric assistance, e-bike sharing attracts a younger and more active user base, resulting in longer travel distances and fewer limitations on service areas. These factors may lead to the formation of larger clusters or communities. On the other hand, bike-sharing trips, relying on human power, are more likely to occur in smaller cluster sizes. The blurring of community boundaries in e-bike sharing may be attributed to the higher level of user activity and the more flexible travel patterns, making it harder to distinguish distinct communities.

5.3. Temporal patterns of e-bike sharing and bike sharing

The analysis of temporal patterns in shared bike and e-bike use reveals distinct morning and evening peaks on weekdays. However, on weekends, the use becomes more sporadic, with ridership evenly distributed throughout the day and no noticeable morning or evening peaks (Fig. 10). The study employs NMF to further explore these fundamental temporal patterns. Fig. 11 and Fig. 12 depict the NMF results for e-bike sharing and bike sharing, respectively, considering the decomposition number of patterns ranging from 2 to 7. Notably, patterns above 3 tend to exhibit repetition and similarities, as seen in Fig. 11c and Fig. 12c. Additionally, when comparing the factorisation loss across different values, an inflexion point occurs at $n = 3$. Consequently, selecting $n = 3$ yields a reasonable and stable factorisation outcome for both transportation modes.

In earlier studies, ride-sharing/car-sharing was observed to exhibit two primary collective patterns: commuting to the workplace in the morning and returning home in the evening (Dong et al., 2018). In contrast, both e-bike sharing and bike sharing exhibit three main

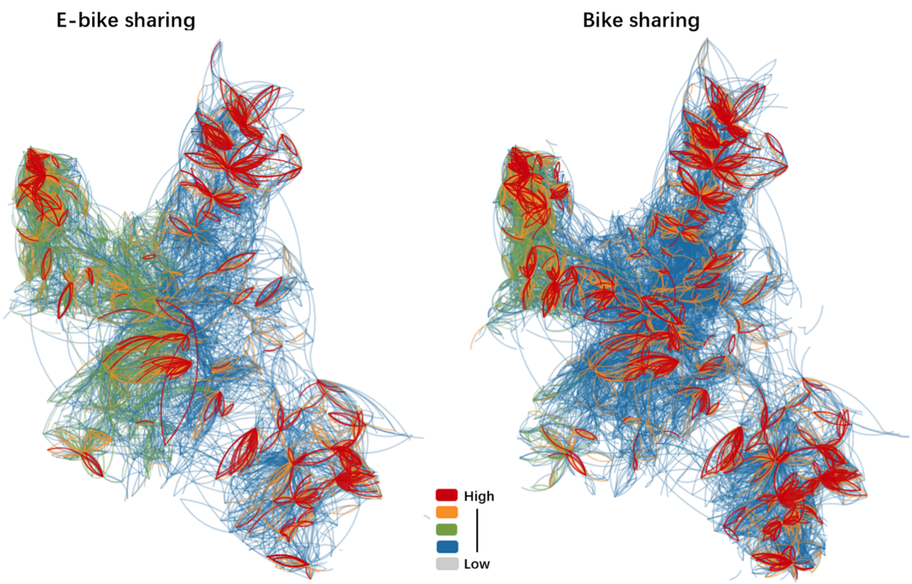

Fig. 7. The bike-sharing trip flow network and e-bike-sharing trip flow network in Kunming.

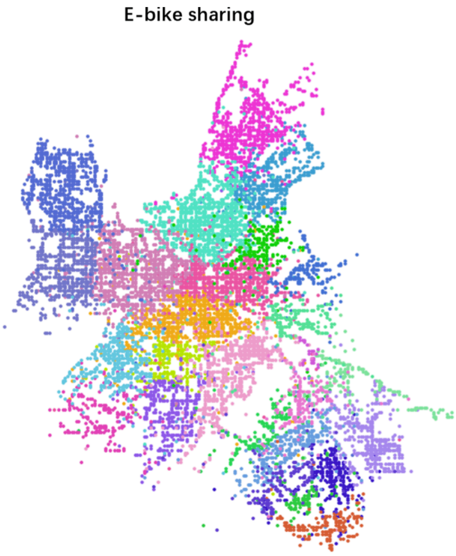

Fig. 8. The cycling neighbourhoods of bike sharing and e-bike sharing (different colours represent different communities).

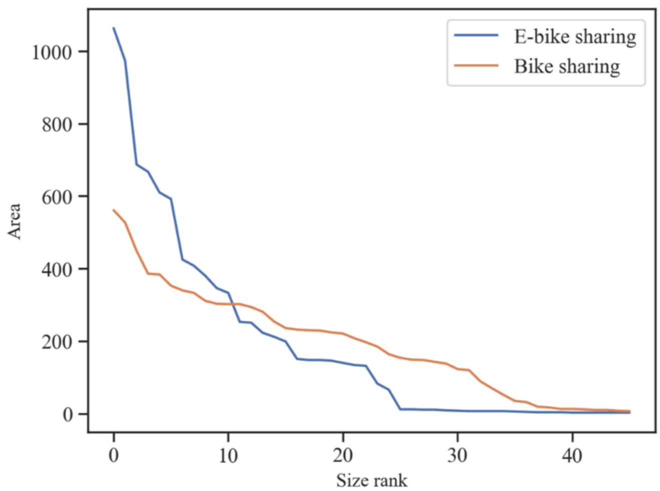

Fig. 9. The size rank of cycling neighbourhoods area of bike sharing and e-bike sharing.

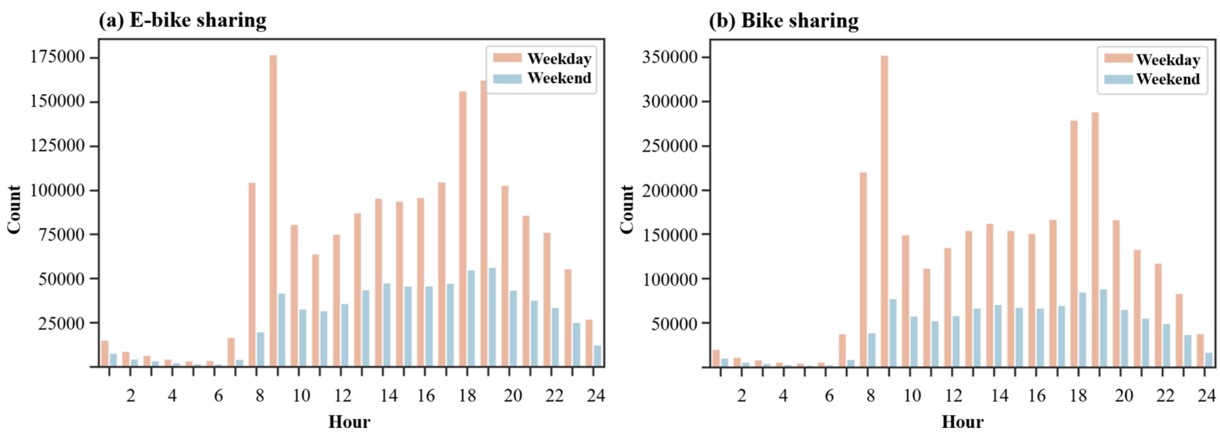

Fig. 10. Temporal pattern of the ridership for shared e-bikes and shared bikes over time.

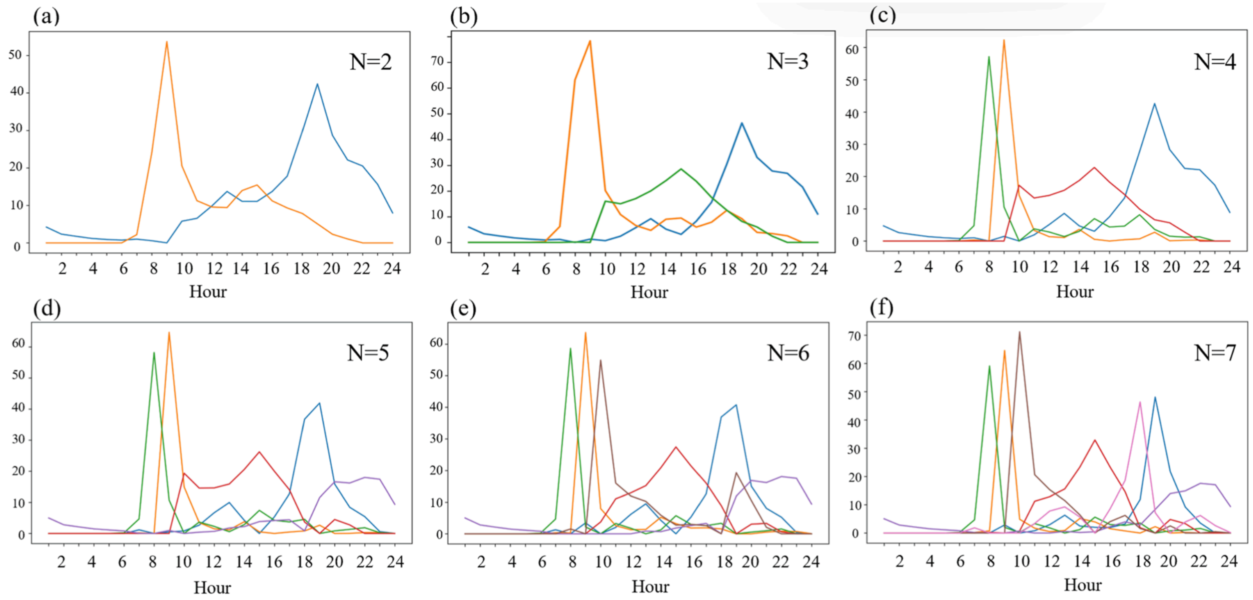

Fig. 11. The basis temporal patterns of **e-bike** sharing trips under different factorisation values.

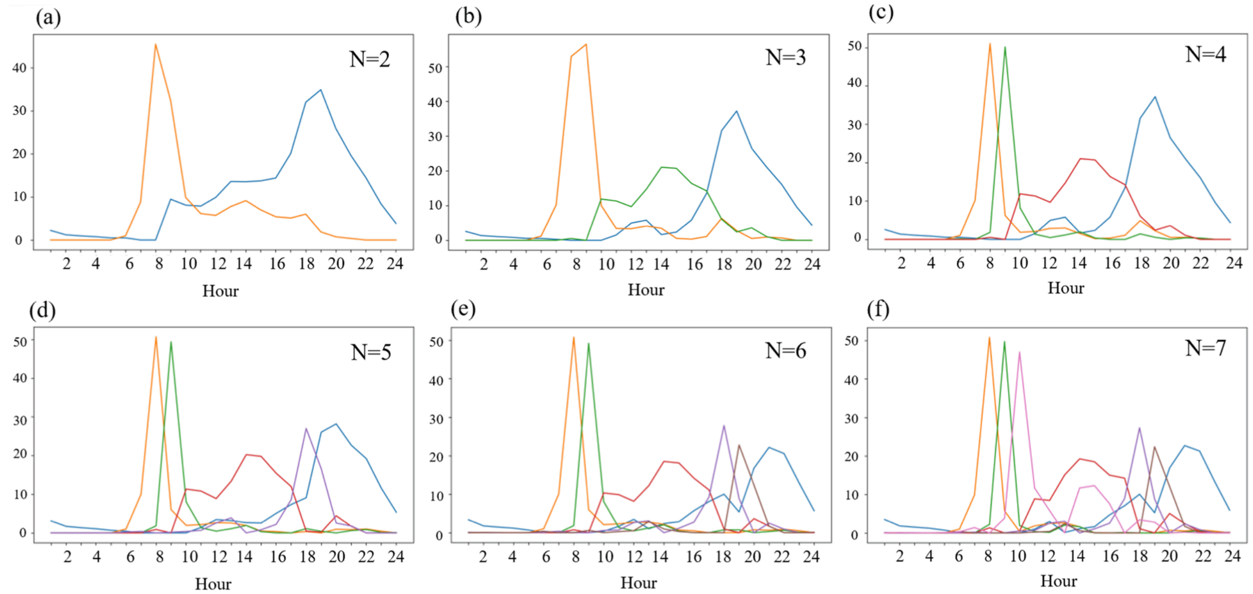

Fig. 12. The basis temporal patterns of **bike**-sharing trips under different factorisation values.

collective patterns (Fig. 13, Fig. A1). Taking e-bike sharing as an example (Fig. 13), the three decomposed patterns can be described as follows: commuting from home to work in the morning (depicted by the orange curve); commuting from the workplace or other places to home in the evening (depicted by the blue curve); random business or recreational travel between two locations (depicted by the green curve). The first and second patterns are related to commuting, while the third pattern represents relatively random activities compared to commuting behaviour. The combination of intensity coefficients for the three collective patterns varies across different locations, resulting in distinct overall temporal patterns in each location. To be specific, if a certain location has a high coefficient for the first basic pattern while the coefficients of the other two are low, it indicates that the location serves as a destination during the morning peak period. Moreover, the land use functions of such locations are likely to be work-related destinations, such as Central Business Districts (CBDs).

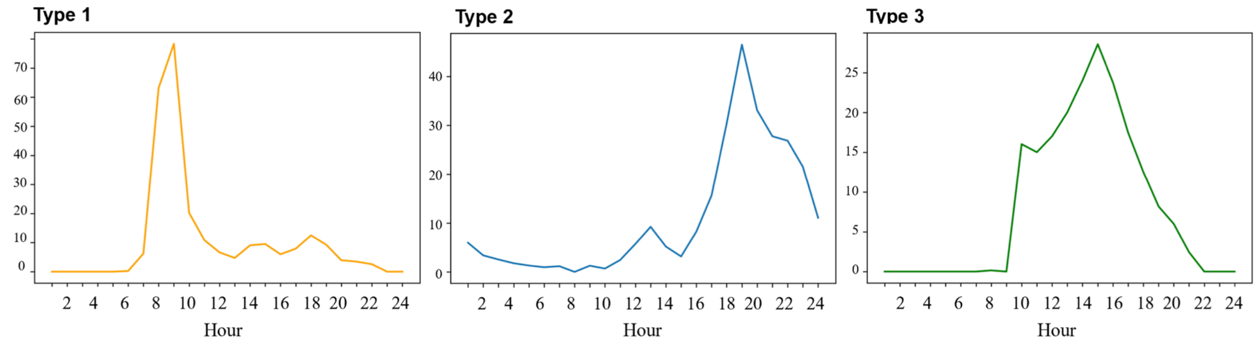

Fig. 13. The three basic patterns of shared e-bikes.

5.4. The correlation between the ridership and the land use function

To gain insights into how the travel purpose changes with the time of day and the potential disparities between shared bikes and e-bikes, this paper examines the correlation between land use density and ridership across various locations in the city at different times of the day. In the correlation analysis (Fig. 14), the horizontal axis represents the time of day (from 7 am to 11 pm), and the vertical axis represents the coefficient of different land use functions. Both bike-sharing and e-bike-sharing ridership exhibit the highest coefficient with subway stations, indicating their strong sensitivity to subway stations (Fig. 14a, b). This association reaches its peak around 8–9 am. To enhance visibility, the study examines the top 1 % OD pair ridership of flow networks for the relationship between trips and subway stations. The findings show a significant concentration of trips around stations situated along subway lines (Fig. 15). Controlling for the socioeconomic indicators, these trips serve as vital connections between the subway stations, residential areas, and workplaces. In the morning, around 8 am, people travel from residential areas to the subway stations, while in the evening, around 7 pm, they commute from workplaces to the subway stations. Additionally, the average distance travelled by shared e-bike users to the subway is approximately 1.8 km, whereas shared bike trips cover an average distance of 1.5 km. This implies that shared e-bikes used for the last-mile connection contribute to expanding the service area of the subway system by facilitating longer journeys.

Due to the high correlation coefficient of subway ridership, which obscures the relationship with other land-use functions, the following graph removed the subway coefficient to examine the relationship between ridership and other land-use functions (Fig. 14c, 14d). For shared e-bike trips, the coefficient of workplace reaches its peak at 9 am, and the coefficient of entertainment activities peaks at 7 pm. Residential areas also exhibit an evening peak at 7 pm (Fig. 14c). The morning rush hour primarily focuses on work-related destinations, while the evening rush hour encompasses more diverse purposes. In contrast, shared bikes show no distinct morning or evening peaks in the elasticity coefficients, particularly for workplaces, where the correlation coefficient remains relatively flat (Fig. 14d). Based on the decomposition of basic travel patterns for shared e-bikes and bikes (Fig. 11b, Fig. 12b), both modes exhibit noticeable commuting peaks at approximately 9 am and 7 pm. This indicates that for commuting purposes, shared e-bikes offer the flexibility and convenience to travel directly to destinations, in addition to connecting subway stations. However, when it comes to commuting purposes, shared bikes are predominantly used to connect subway stations rather than for direct travel to destinations.

6. Conclusion

6.1. Concluding remarks

Using real-operation big data in Kunming, China, this research represents a comprehensive study to investigate and compare the travel patterns of shared dockless e-bikes and bikes. We found that shared bikes and e-bikes are quite similar in many aspects, such as user age, spatial distribution, and basic time patterns, along with minor differences. This study identified three main peak uses of dockless e-bikes and bike sharing during the day but revealed diversified location preferences, indicating different travel purposes. Despite these similarities, there are some differences. E-bikes tend to be used for longer trips and durations, have a higher frequency of use, and their networks are more dispersed, showing greater utilisation and turnover compared to shared bikes. Additionally, within e-bike sharing systems, commuting activities follow two patterns: direct travel to the destination or integration with public transit. On the other hand, shared bikes mainly rely on public transit transfers for commuting. Overall, the results showed the similarities and differences in the travel pattern between purely physical activity-based bike sharing and electric-assist bike sharing within the dockless micro-mobility sharing systems.

6.2. Academic contribution and policy implications

The findings offer valuable insights into the similarities and differences between these two transportation modes, providing actionable information for operators, policymakers, and urban planners. The results related to the use characteristics of shared e-bikes and bikes are similar to previous survey-based or big data-based studies, showing longer travel distances and duration and higher riding speeds of shared e-bike trips than that of shared bikes (Shen et al., 2018; Bourne et al., 2020; Ye et al., 2021), longer distances for

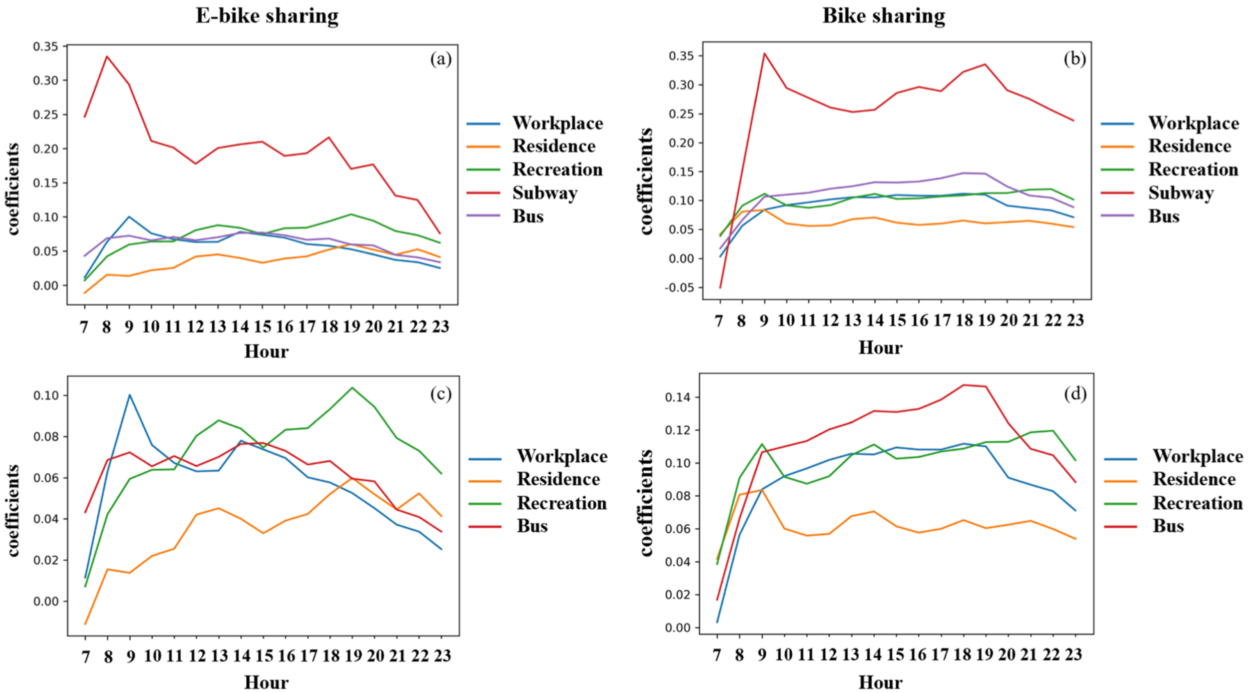

Fig. 14. Temporal distribution of elasticity coefficients of the explanatory variables (graphs a and b show all the land-use functions, while c and d depict the remaining land-use functions after the removal of the subway).

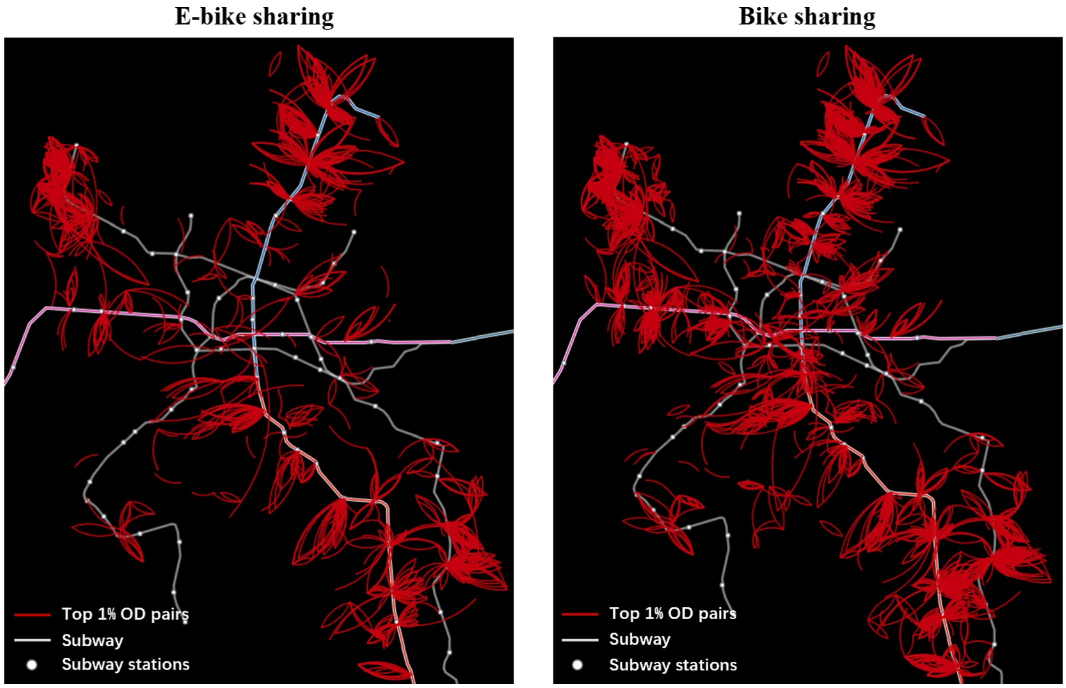

Fig. 15. The distributions of the top 1% ridership of OD pair in flow networks.

younger adults than older adults (Kroesen, 2017), and younger user demographics of e-bike sharing (Ye et al., 2021). Nonetheless, this study uncovered higher frequency use for dockless shared e-bikes than shared bikes. These results indicated that electronic-powered bike sharing could save the users' physical energy, thus improving travel and commuting efficiency. Regarding the spatio-temporal patterns of e-bike and bike riding, the findings are also consistent with existing studies by demonstrating the close relationship between bike and e-bike riding with subway stations (Global and Planning, 2017; Fan & Zheng, 2020; Ye et al., 2021), and revealing the more alternative role of shared e-bikes as utilitarian transport mode for short- and medium-distance car trips (Haustein & Møller, 2016; Ioakimidis et al., 2016; Moser et al., 2018). Apart from these overall characteristics, this study also presented detailed hour-by-hour spatial preferences for shared bike and e-bike riding, and showed the increasing utilitarian role of e-bikes from morning to night. Compared to other studies, the main innovation of this research lies in the characterisation of the spatial network patterns for shared e-bikes and bikes, and sheds light on the densely connected clusters of the flow of shared bikes and more dispersed distribution and bigger community of e-bike sharing. This result suggested an extended commuting radius and more flexible travel patterns within e-bike sharing systems, and their potential to enhance the connection between different communities far away from each other.

In light of previous research highlighting concerns regarding heightened riding risks and the concurrent decrease in the utilisation of alternative modes of public transit consequent to the introduction of shared e-bike systems, this study assumes a pivotal role in furnishing insights conducive to the formulation of rigorous regulatory frameworks governing the operation of shared e-bike systems. The findings indicate longer travel distances and a higher potential to travel directly to destinations of shared e-bike sharing, suggesting a potential strategy for deploying additional shared e-bike resources to accommodate the demand for long-haul travel in areas characterised by diminished accessibility to conventional modes of public transportation. Conversely, within urban hubs, it is recommended that regulatory measures be enacted to delimit the use of e-bikes in densely populated locales or during peak periods, a measure that could be facilitated through coordinated oversight by shared e-bike operators. Considering the synchronicity observed in temporal utilisation patterns between shared e-bikes and conventional bicycles, particularly during periods of peak demand, juxtaposed with the proliferation of food delivery e-bikes and other electric vehicles on urban thoroughfares, it is plausible to infer a commingling of shared e-bikes and bikes that may substantially elevate accident rates and associated riding hazards. Consequently, it is imperative to devise remedial measures aimed at enhancing the safety and convenience of cycling environments. For instance, urban planners may opt to designate segregated lanes exclusively for e-bikes and bicycles, with the potential for the e-bike lanes to evolve into dedicated corridors for autonomous transportation as advancements in autonomous driving and robotics materialise. Concurrently, collaboration between e-bike sharing entities and traffic regulatory authorities could prove instrumental in disseminating educational initiatives, providing guidance, and enforcing adherence to traffic regulations and safe riding practices among users, facilitated by the integration of ride trajectory tracking capabilities within shared e-bike platforms interfacing with users via dedicated mobile applications. Moreover, recognising that people tend to use shared bikes for commuting to subway stations, integration with public transit systems should be emphasised to enhance first-mile and last-mile connectivity. Policymakers can focus on improving infrastructure and facilities around transit hubs to facilitate seamless transitions between biking and public transportation, particularly subway stations, to boost their potential for environmental benefits, such as increasing parking space, installing e-bike parking, and charging integrated piles.

6.3. Limitations

There are some limitations to this study. Firstly, the findings of this study are based on the analysed city. Different cities have unique characteristics that may influence the travel pattern results. This work could be extended by obtaining bike-sharing data and land use data from other cities to examine and cross-compare the differences in travel patterns. Secondly, this study did not analyse the differences in travel patterns among different age groups, genders, regular users, and non-regular users. Future research can further explore the use preferences and patterns of users with different attributes. Finally, limited by the availability of data, the analysis relies on e-bike sharing and bike sharing datasets, not including public transit trips, car trips, and other transportation modes data. Future studies should strive to obtain more comprehensive and reliable data to strengthen the analysis for comprehending the situations in which they can be integrated into existing transportation networks, such as the interaction between (electric) bike-sharing and public transport.

CRediT authorship contribution statement

Qiumeng Li: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Enjia Zhang:** Writing – review & editing, Visualization, Data curation. **Davide Luca:** Writing – review & editing, Supervision. **Franz Fuerst:** Writing – review & editing, Supervision.

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.

Appendix

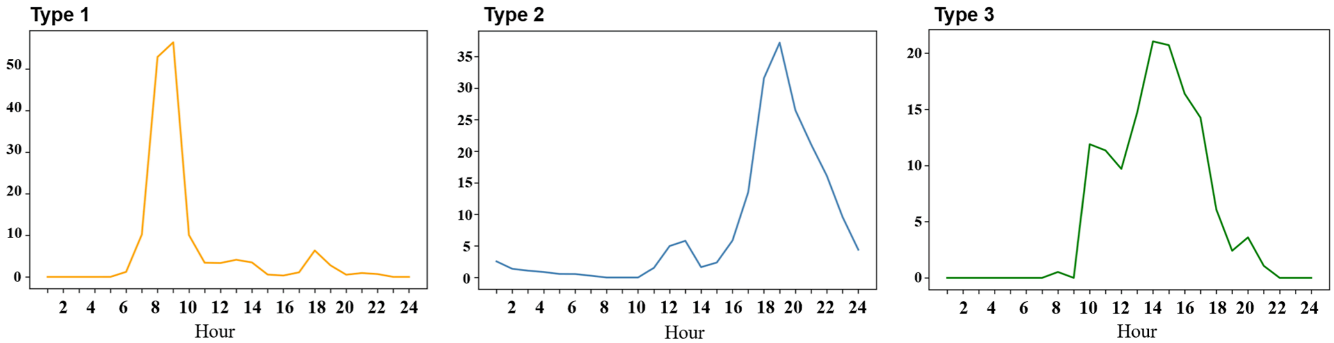

Fig. A1. The three basic patterns of shared bikes

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