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

Abstract:

To facilitate the tailoring of dockless bike-sharing and electric bike (e-bike) sharing services and aid policymakers 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, firstly, there is a discernible preference among younger individuals for e-bike sharing in comparison to shared bikes. Secondly, 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. Thirdly, both shared bikes and shared e-bikes have three basic temporal patterns for commuting and recreational purposes. Finally, the commuting activities within e-bike sharing systems exhibit two patterns: direct travel to the destination or integration with public transit. In contrast, shared bikes predominantly rely on public transit transfers for commuting purposes.

Keywords: shared micro-mobility, spatio-temporal travel pattern, network structure, trip purposes, big data mining

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 percent 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 expand the potential user base by accommodating a wider range of individuals, including older adults, less physically fit individuals, and those with longer commuting distances. 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).

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. Due to the differences between bike sharing and e-bike sharing modes, spatio-temporal preferences for their usage may also vary. Understanding the spatio-temporal travel patterns differences inside shared micro-mobility is crucial for effectively designing, optimizing, and planning different systems, allowing for the customization of different shared micro-mobility services to better meet user needs and preferences. 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 behavior 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 usage of docked bikes, docked e-bikes, and dockless e-bikes before and after the COVID-19 pandemic (Li et al., 2021). Nevertheless, 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 giving 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 program 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 of 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 has been selected as the study case due to both shared e-bikes and shared bikes operate within the same operational space, which enables a straightforward comparison of travel behaviours on a consistent spatio-temporal condition. 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.

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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 factorization 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 summarizing 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 behavior 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 behaviors among different shared vehicles also have gained great interest. For example, Li et al., (2021) contrasted the usage and travel behavior of various shared vehicles (i.e., docked bikes, docked e-bikes, dockless e-scooter, and dockless e-bikes) before and after the onset of the pandemic. McKenzie, (2020) distinguished usage patterns, peak usage 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 spatiotemporal 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 behavior and spatial patterns of bike sharing and e-bike sharing, highlighting their distinct characteristics.

2.2 The usage characteristics of shared bike and e-bike systems

The state-of-art research investigated and compared the spatio-temporal characteristics of the usage 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.,
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 usage 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 & 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 usage decreases as age increases (Kroesen, 2017). 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 usages

Bike sharing and e-bike sharing, as new modes of transportation, can change individuals’ travel behaviors. 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 complementing 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 analyzing the flow characteristics of transportation systems by dividing them into geographic units (A. Li et al., 2021; Xie et al., 2021; Yildirimoglu & Kim, 2018). Austwick et al. (2013) utilized 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 decentralized 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. 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 behavior between bike and e-bike sharing are still under-ananswered.

2.4 Summary

Overall, previous research exhibits two primary limitations. Firstly, there is a scarcity of research that investigates 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 currently 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 at 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 pattern 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 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 utilization 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 usage 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.

Table 1. Example of bike sharing trip records.

<table>
<thead>
<tr>
<th>Order id</th>
<th>City</th>
<th>Date</th>
<th>User id</th>
<th>Bike id</th>
<th>Gender</th>
<th>Age</th>
<th>Register date</th>
<th>Origin (longitude, latitude)</th>
<th>Destination (longitude, latitude)</th>
<th>Start Time</th>
<th>End Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip No. 1</td>
<td>Kunming</td>
<td>2021-03-05</td>
<td>6939</td>
<td>7405</td>
<td>Male</td>
<td>26</td>
<td>2020-06-02</td>
<td>102.42, 25.02</td>
<td>102.13, 24.32</td>
<td>17:20</td>
<td>18:02</td>
</tr>
</tbody>
</table>
4. Methods

This study takes the 100m*100m 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, the study provides an overview of trip attributes, including the distribution of user age, trip distance, duration, and usage frequency. 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 nonnegative matrix factorization (NMF) method is employed to decompose temporal patterns and unveil fundamental trip purposes. Finally, elasticity analysis is utilized 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 Figure 2.

Fig. 2. Research framework

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. Take the flow network of shared bikes for example. 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 Infomap algorithm 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.

The Infomap algorithm is based on the Map equation and employs random walk and Huffman coding for community detection. This algorithm partitions the communities based on the patterns of connections within a given directed and weighted graph. To assess the local connectivity or clustering of nodes, the average clustering coefficient is used as an index. 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 factorization 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 to 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 factorization. In NMF, a nonnegative matrix is decomposed into two lower-rank nonnegative 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 factorization that best captures the underlying structure of the data. This is achieved by minimizing 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, the 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 100m*100m 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 ∈ [1, b] ∩ ℤ and j ∈ [1, d] ∩ ℤ. h is the time slot from 1 to 24 a day, and h ∈ [1,24] ∩ ℤ. Therefore, a 1 × h vector $G_{i,j}$ 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 × h vectors are defined to represent basis collective patterns with normalized numbers of trips along time h: $T_1$, $T_2$, ..., $T_n$; n is the number of pattern types that we initially set up to decompose. To be more specific, the factorization formula can be written as:
\[
\begin{bmatrix}
G_{1,1} \\
G_{1,2} \\
\vdots \\
G_{1,d} \\
G_{2,1} \\
G_{2,2} \\
\vdots \\
G_{b,d}
\end{bmatrix} = \begin{bmatrix}
S_{1,1} \\
S_{1,2} \\
\vdots \\
S_{1,d} \\
S_{2,1} \\
S_{2,2} \\
\vdots \\
S_{b,d}
\end{bmatrix} \begin{bmatrix}
T_1 \\
T_2 \\
\vdots \\
T_n
\end{bmatrix}
\]

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 \( G \in \mathbb{R}^{bd \times h}_+ \) in location \((i,j)\) can be factorized into two low-rank nonnegative factors, then we could get the basis patterns \( T \in \mathbb{R}_+^{n \times h} \) and the coefficients \( S \in \mathbb{R}^{bd \times h}_+ \) 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:

\[ G = ST \]

### 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 100m*100 m grids and the model is established as follows:

\[
\ln Y_{i\ell} = \beta \ln X_{i\ell} + \gamma_i + \alpha
\]

Where \( Y_{i\ell} \) is the total ridership of e-bike sharing or bike sharing in grid \( i \) at hour \( \ell \) (from 7 am to 11 pm), \( X_{i\ell} \) is the intensity of one land use type in grid \( i \), indicated by POI density, and \( \gamma_i \) is a set of control variables, such as population density and intensity of economic activity represented by the night light index. The elasticity value (\( \beta \)) is used to indicate the sensitivity degree of each land use function to the ridership, meaning that a 1% change in \( X \) is associated with a \( \beta \% \) change in \( Y \). While such kind of analysis is not able to identify the causal effect of
regressors on total ridership, it anyway provides interesting exploratory insights. Elasticities are in fact extensively employed in economic and urban planning research, as the 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 sharing and bike sharing, as well as the differences between them. It includes a basic description of trip attributes, temporal patterns, flow network structures, and the correlations between ridership and land use functions.

5.1 Basic description

The travel distance and duration

Fig. 3 presents the trip distance and duration for e-bike sharing and bike sharing. 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 minutes, while shared bikes have an average of 15.08 minutes. In general, the trip distance and duration of shared e-bikes are 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 compared to 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.
The usage frequency serves as a measure of the efficiency of shared e-bike and shared bike usage, reflecting fleet utilization 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. 4, the usage frequency of shared e-bikes and shared bikes is 22.18 times per week and 17.73 times per week, respectively. The vehicle utilization 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.
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, 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 of e-bike sharing attracting a younger demographic. E-bikes are often perceived as a modern and technologically advanced mode of transportation, which may appeal more to younger individuals who are more inclined to embrace new technology.

![Frequency distribution of age](image)

**Fig. 5 The frequency distribution of age**

Both bike sharing and e-bike sharing exhibit a similar age structure trend that fluctuates throughout the day (Fig. 6). 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 that of bike sharing throughout the day.
Fig. 6 The distribution of users’ ages for e-bike sharing and bike sharing throughout the day

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.

The clustering coefficient is a commonly used measure in network analysis that quantifies the tendency of nodes to form clusters or communities. 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.

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

To make the network structure clearer, the paper applies 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 sharing 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.
Fig. 9. The size rank of cycling neighbourhoods area of bike sharing and e-bike sharing

5.3 Temporal patterns of e-bike sharing and bike sharing

The analysis of temporal patterns in shared e-bike usage reveals distinct morning and evening peaks on weekdays (Fig. 10). However, on weekends, the usage becomes more sporadic, with ridership evenly distributed throughout the day, and no noticeable morning or evening peaks. Fig. 10 provides an overview of the overall time pattern across the entire city, although different locations exhibit diverse temporal patterns. These location-specific patterns are a linear combination of several fundamental patterns, which also could reflect the primary travel purposes. In the subsequent analysis, the study employs Nonnegative Matrix Factorization to further explore these fundamental temporal patterns. NMF is a machine learning technique employed for the purpose of matrix factorization. Its primary objective is to identify an optimal factorization that effectively captures the inherent structure within the given dataset. By decomposing the nonnegative matrix into basis and coefficient matrices, NMF can identify underlying temporal patterns of ridership in the shared bike and shared e-bike trip data.

Figures 11 and 12 depict the NMF factorization 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 factorization loss across different values, an inflection point
occurs at n=3. Consequently, selecting n=3 yields a reasonable and stable factorization outcome for both transportation modes.

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

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

Fig. 12. The basis temporal patterns of bike sharing trips under different factorization values
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 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](image)

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

To gain insights into 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 1.8km, whereas shared bike trips cover an average distance of 1.5km. **This implies that shared e-bikes contribute to expanding the service area of the subway system by facilitating longer journeys.**

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)
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-d). 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 can conclude several main findings: (1) The analysis revealed slightly longer trip distances and durations, higher use frequency, greater utilisation and turnover, and more dispersed networks of e-bike fleets than shared bikes. (2) This study identified three main peak usage of dockless e-bikes and bike sharing during the day, but revealed diversified location preferences, indicating different travel purposes. (3) This study suggested that shared e-bikes were found to contribute to expanding the service area of the subway system by enabling longer journeys, and enabling users to travel directly to their destinations. Overall, the results showed the mode choice and travel behaviour differences between physical activity-based bike sharing and electronic-powered e-bike sharing in 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 usage 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 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 usage 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 statins
(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 characterization of the spatial network patterns for shared e-bikes and bikes, and shed light on the densely connected clusters of 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.

Considering the higher usage frequency of shared e-bikes and their potential to replace medium- and long-distance transportation modes, policymakers should consider promoting e-bike sharing to alleviate traffic congestion and enhance urban mobility. In addition, understanding the age demographics and preferences of users is crucial for targeted marketing and outreach efforts. Given that e-bike sharing tends to attract a younger demographic compared to bike-sharing, promotional campaigns, and incentives can be tailored to attract a wider range of users, including older individuals who may benefit from the convenience and assistance of e-bikes. To support the growth of e-bike sharing and bike sharing, adequate infrastructure should be provided, such as dedicated bike lanes, parking facilities, and charging stations for e-bikes. Compared to bike sharing, the dispersed nature of e-bike sharing networks suggests the need for a well-distributed infrastructure to support the system. Planners should consider providing adequate cycling facilities and charging facilities across a wider area to accommodate the extended commuting radius. Based on the size of cycling neighbourhoods, operators can optimize fleet reallocation and redistribution strategies for both e-bike sharing systems and bike sharing systems. Recognizing that people tend to use shared bikes for commuting to subway stations, integration with public transit systems should be emphasized 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 usage 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.

References


Electronic copy available at: https://ssrn.com/abstract=4628673


Wang, Y., & Sun, S. (2022). Does large scale free-floating bike sharing really improve the


Appendix

Fig. A1. The three basic patterns of shared bikes