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Multi-modal Travel Simulation and Travel Behavior Analysis: Case Study in Shanghai

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Abstract: This study aims to investigate the multi-modal travel behavior and obtain quantitative results for various indicators by building an eqasim/MATSim model, using Shanghai as the study area. Travel demand is mainly generated using mobile phone signaling data. For each mode, a travel cost model is formulated. Additionally, an MNL (Multinomial Logit) model is integrated into eqasim through the DMC (Discrete Mode Choice) module. The results demonstrate that using mobile phone signaling data to generate travel demand yields a high-quality representation of travel demand. Users prefer public transport over cars when travel distances are similar. Furthermore, for longer-distance travel, the combined bus and subway mode significantly reduces walking distance, travel time, and travel costs. The spatial accessibility of public transport strongly depends on the availability and coverage of the public transport infrastructure. In areas where public transport services are limited, cars can complement public transport by providing accessibility to areas with scarce public transport options. From a transportation system perspective, car trips during rush hours are similar to public transport and biking, while walking is consistently used throughout the day due to the shortest travel time. Home-based trips, particularly commuting trips, have the highest share. Understanding these travel patterns is essential for optimizing transportation planning and effectively addressing peak-hour travel demand. This study demonstrates the effectiveness of using mobile phone signaling data for studying multi-modal travel behavior. The results provide valuable insights for transportation planners and policymakers in developing efficient and sustainable transportation systems that meet the preferences and needs of travelers.

Key words: traffic engineering; multi-modal travel; mobile phone signaling data; eqasim/MATSim simulation; MNL(Multionmial Logit) model; travel behavior analysis

1 Introduction

Multi-modal travel refers to users selecting the most suitable travel mode and route based on real-time conditions during different stages of their trip. To study urban traffic travel behavior and obtain quantitative analysis results for indicators like travel costs, distances, times, and activity patterns, researchers typically employ travel behavior models and simulations[1-2]. For large-scale application scenarios, there is a common method for conducting corresponding analyses, agent-based simulations[3].

Several popular travel simulation software options exist, encompassing traffic network modeling, travel behavior modeling, and traffic flow analysis. Examples include MATSim (Multi-Agent Transport Simulation)[4], SUMO (Simulation of Urban Mobility)[5], and TransModeler[6]. These simulations enable the analysis of complex interactions between different elements of the transportation system and users' travel choices, leading to more effective transportation solutions.

MATSim stands out as a powerful simulation tool capable of accurately modeling the detailed operation process of a transportation system. This comprehensive approach enables MATSim to simulate travel behavior with precision and capture the interactions between different travel modes effectively. One of MATSim's strengths lies in its ability to study changes in travel behavior based on individual travel purposes and travel times. HÖRL[7] introduced eqasim which facilitates a seamless path from raw data generation to mobility simulation. It can handle discrete mode choice and efficiently simulate large-scale daily activities[8].

Although a lot of research work have been conducted on travel behavior analysis, there are still many chal-

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lenges, which impact our understanding of multi-modal travel. Firstly, a significant challenge is the difficulty of integrating data from multiple sources due to the lack of standardized data formats among different data providers. Secondly, the complexity of multi-modal travel models is another hurdle. Such models must account for various factors, including the different stages involved in the travel process, the choice of travel modes, routes, traffic conditions. These uncertainties can significantly impact individuals' travel decisions. To address these challenges, researchers need to develop standardized data formats for merging data from diverse sources. Additionally, there is a need to work on refining multi-modal travel models, incorporating real-time data and leveraging agent-based simulations.

Mobile phone signaling data has emerged as a valuable resource for studying travel behavior[9]. It an replacs the traditional use of census data to generate travel demand. This switch allows for a more up-to-date and comprehensive analysis of travel behavior. By utilizing mobile phone signaling data, researchers can study the individual multi-modal travel process and analyze the factors influencing an individual's travel choices.

This study is conducted in Shanghai, employing eqasim as the underlying simulation framework. The fuse mobile phone signaling data are used to generate travel demand. The analysis of travel behavior is approached from two perspectives. From the users' perspective, it examines travel costs, travel distances, and spatial accessibility. From the system perspective, the distribution of trip starts and end times, shedding light on peak travel periods and patterns, and the relationship between trips and activity types is explored. This research contributes to a more comprehensive understanding of multi-modal travel in urban transportation within the studied area.

The remainder of this article is structured as follows. Section 2 presents the data and study area. Section 3 describes the eqasim simulation framework and research methodology. In Section 4, the results are presented. Finally, the conclusion of this work is provided.

2 Data

2.1 Travel demand

The mobile phone signaling data is provided by a mobile company in Shanghai. Indeed, the use of mobile phone signaling data must be accompanied by rigorous anonymization measures to ensure the protection of sensitive user information and maintain privacy. This step is crucial to adhere to ethical and legal standards. After anonymization, data pre-processing becomes essential to handle redundant and erroneous information and address any missing data. This process aims to obtain valid and reliable data for further analysis. The processed data is then employed to generate travel demand. The workflow for data pre-processing and travel demand generation is illustrated in Figure 1. In order to obtain data with travel modes and activity types, this study integrated mobile phone signaling data with resident travel survey data, urban spatial data, etc. to construct a travel stay chain[10].

To accommodate the running time limitations of MATSim, the simulation employs a small sample dataset, and some configurations are scaled down to match the sample size used in this paper. As a consequence, the analysis utilizes mobile phone signaling data collected for a typical work day. From this dataset, a total of 400,000 trips are extracted to serve as the travel demand, representing a 1.5% sample of the residents.

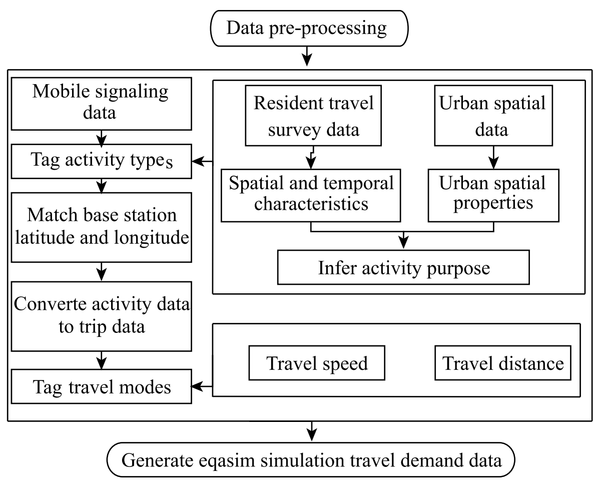

Fig. 1 Data convert flow

2.2 Supply data

The area within the outer ring road of Shanghai serves as the research area (Figure 2). This region boasts a relatively dense distribution of base stations, enabling the observation of users' location shifts with a minimum accuracy of 100 m.

The road network, comprising nodes and links is extracted from the OpenStreetMap (OSM)[11]. Utilizing the General Transit Feed Specification (GTFS)[12] data standard, we incorporate the public transport routes and station data to generate the GTFS data. This data is then integrated with the road network. To generate the multi-modal road network data, which includes the public transport network, the public transport vehicle and schedule information, we employ the pt2matsim package[13].

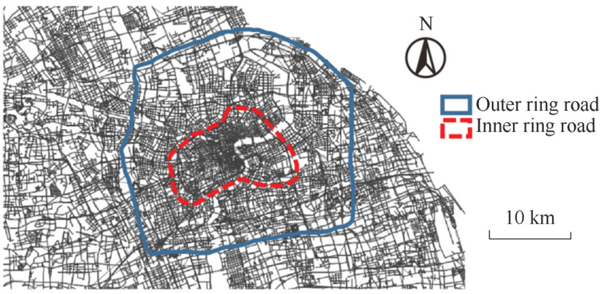

Fig. 2 Shanghai road network topology map

3 Simualtion

3.1 eqasim framework

Based on MATSim, eqasim introduces new functionality. MATSim is an agent-based simulation framework in which each agent tries to maximize its daily score for a specific activity plan using an iterative, co-evolutionary learning approach. In eqasim, the Scoring part used in the Replanning phase is removed, and a DMC (Discrete Mode Choice) extension module is introduced[8]. The DMC extension provides support for travel mode choice using a discrete choice model. As a result, various variables related to different travel modes can be taken into account, such as travel time, waiting time and travel cost.

The *eqasim-java* package[7] provides utilities for the discrete mode choice model (DMC). The main components of this model are depicted in Figure 3. The "Estimator" assesses the utility of each mode defined in the DMC. The "Predictor" calculates or predicts the "Variables". Furthermore, the "Estimator" encompasses the "Cost model" and relevant "Coefficients" of the variables. The utility can be calculated using a Multinomial Logit (MNL) model. Once calculated, the utility is passed to the DMC to determine the probability for each mode. Subsequently, a travel mode is selected for a specific agent.

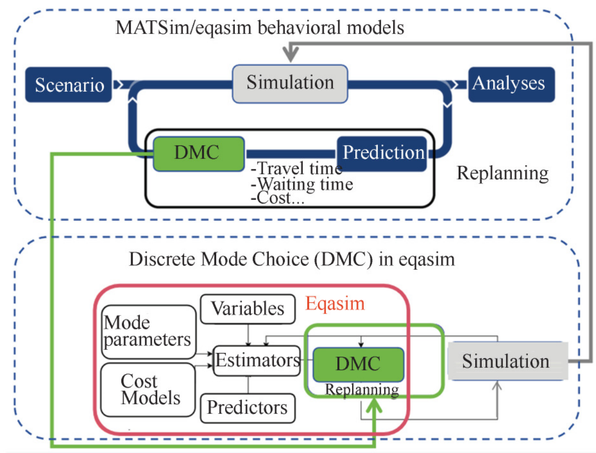

Fig. 3 Eqasim structural framework[7]

3.2 Travel cost model

Each mode necessitates a travel cost model, which quantifies the expenses incurred by individuals when using different travel modes. The travel cost calculations for each mode are derived from pertinent statistical references[14-15], and are presented below. Equations (1) and (2) outline the models for car and public transport (bus and subway) respectively. As for bike and walk, their travel costs are assumed to be zero.

$$x_{\mathrm{ctc}} = c_{\mathrm{car}} \cdot d_{\mathrm{ctd}}, \tag{1}$$

$$x_{\mathrm{ptc}} = \begin{cases} 2.0, & d_{\mathrm{btd}} > 0 \\ 3.0, & 0 < d_{\mathrm{std}} \leqslant 6\ \mathrm{km} \\ 4.0, & 6\ \mathrm{km} < d_{\mathrm{std}} \leqslant 16\ \mathrm{km} \\ 5.0, & 16\ \mathrm{km} < d_{\mathrm{std}} \leqslant 26\ \mathrm{km} \\ 6.0, & 26\ \mathrm{km} < d_{\mathrm{std}} \leqslant 36\ \mathrm{km} \\ 7.0, & 36\ \mathrm{km} < d_{\mathrm{std}} \leqslant 46\ \mathrm{km} \\ 8.0, & 46\ \mathrm{km} < d_{\mathrm{std}} \leqslant 56\ \mathrm{km} \\ 9.0, & d_{\mathrm{std}} > 56\ \mathrm{km} \end{cases}, \tag{2}$$

Where, x_{ctc} represents the cost value of the car, which is calculated as a linear function of distance traveled, and $c_{\mathrm{car}} = 2.37$ CNY/km is the unit cost for car trips; x_{ptc} represents the cost value of the public transport, which is calculated based on distance-based sectional charges for both bus and subway travel; d_{btd} denotes the cost associated with the bus trip, which depends on the distance traveled, and d_{std} denotes the cost associated with the subway trip.

3.3 Mode choice model

The mode choice model is employed to elucidate the trade-offs individuals encounter while making decisions.

The utility formulations for each mode are presented in Equation (3) to (6). These functions encompass variables and parameters, with the parameters derived from DUAN[16] based on the RP and SP surveys conducted in Shanghai. The specific parameter values are detailed in Table 1.

$$U_{\mathrm{car}} = \alpha_{\mathrm{car}} + \beta_{\mathrm{civt}} \cdot x_{\mathrm{civt}} + \beta_{\mathrm{ctc}} \cdot x_{\mathrm{ctc}}, \tag{3}$$

$$U_{\mathrm{pt}} = \alpha_{\mathrm{pt}} + \beta_{\mathrm{pivt}} \cdot x_{\mathrm{pivt}} + \beta_{\mathrm{ptc}} \cdot x_{\mathrm{ptc}} + \beta_{\mathrm{paed}} \cdot x_{\mathrm{paed}} + \beta_{\mathrm{pwt}} \cdot x_{\mathrm{pwt}}, \tag{4}$$

$$U_{\mathrm{bike}} = \alpha_{\mathrm{bike}} + \beta_{\mathrm{btd}} \cdot x_{\mathrm{btd}}, \tag{5}$$

$$U_{\mathrm{walk}} = \alpha_{\mathrm{walk}} + \beta_{\mathrm{wtd}} \cdot x_{\mathrm{wtd}}, \tag{6}$$

Where, U_{car}, U_{pt}, U_{bike}, U_{walk} represent the utilities of the car, public transport, bike, and walk, respectively. α_{car}, α_{pt}, α_{bike}, α_{walk} denote the alternative specific constants for each mode, representing the unobserved factors that influence mode preferences. β_{civt} and β_{pivt} are the marginal utility parameters for in-vehicle time for each mode. β_{pwt} is the marginal utility parameters for waiting time. β_{paed} is the marginal utility parameters for access/egress distance. β_{ctc} and β_{ptc} are the marginal utility parameters for travel cost for the car and public transport, respectively. β_{btd} and β_{wtd} are the marginal utility parameters for trip distance for the bike and walk, respectively. The mode choice variables x include in-vehicle time, waiting time, access/egress distance, travel cost and trip distance with the units of measurement as minutes, kilometers, and CNY (Chinese Yuan) respectively.

Table 1 Discrete mode choice of model parameters

Mode	Parameter	Calibrated
Car	α_{car}	5.500 3
	β_{civt}	−0.044 4
	β_{ctc}	−0.019 5
Public transport	α_{pt}	7.499 8
	β_{pivt}	−0.017 3
	β_{ptc}	−0.019 5
	β_{pwt}	−0.133 0
	β_{paed}	−0.477 4
Bike	α_{bike}	6.999 8
	β_{btd}	−0.292 2
Walk	α_{walk}	8.412 1
	β_{wtd}	−0.292 2

4 Calibration

To address the issue of the increased attractiveness of walking, the following adjustment is made to the walk utility formulation, Equation (7). By incorporating this penalty term into the utility formulation, the model can more accurately account for the increased unattractiveness of walking for longer distances, making it a better representation of real-world travel behavior.

$$U'_{\mathrm{walk}} = U_{\mathrm{walk}} - \exp\left[\ln(\omega) \cdot \frac{x_{\mathrm{wtd}}}{\theta_{\mathrm{wt}}}\right], \tag{7}$$

Where, U'_{walk} represents the adjusted utility of the walk. θ_{wt} is the walking distance threshold, we chose 10 km for this study. This threshold means that for trips shorter than 10 km, the penalty term is close to zero. ω is the penalty parameter for longer-distance walking, set to 100 for this work. This parameter determines the rate at which the penalty term increases exponentially as the walking distance exceeds the threshold θ_{wt}.

Furthermore, to achieve a good model fit, the alternative specific constant needs to be adjusted.

After completing the calibration process, the mode choice model's parameters have been fine-tuned, and the calibrated values are presented in Table 1. Additionally, Figure 4 displays a comparison of the mode shares obtained from travel survey data with the simulated results. The graph demonstrates that the calibrated curve closely aligns with the reference data, indicating a good fit between this model and the real-world observations. The overall trip shares for each mode, based on the calibration and simulation, are as follows: car (22.7%), public transport (39.8%), bike (28.1%) and walk (9.5%), respectively.

These percentages represent the proportion of total trips made using each mode based on the calibrated mode choice model. The high level of agreement between the calibrated model and the reference data indicates that the mode choice model is performing well and accurately capturing the preferences and behavior of individuals in the study area. It can now be reliably used to simulate multi-modal travel behavior choices.

5 Results and analysis

5.1 User perspective

(1) Trips and travel cost

By comparing the total cost across different modes, researchers can gain insights into how cost influences us-

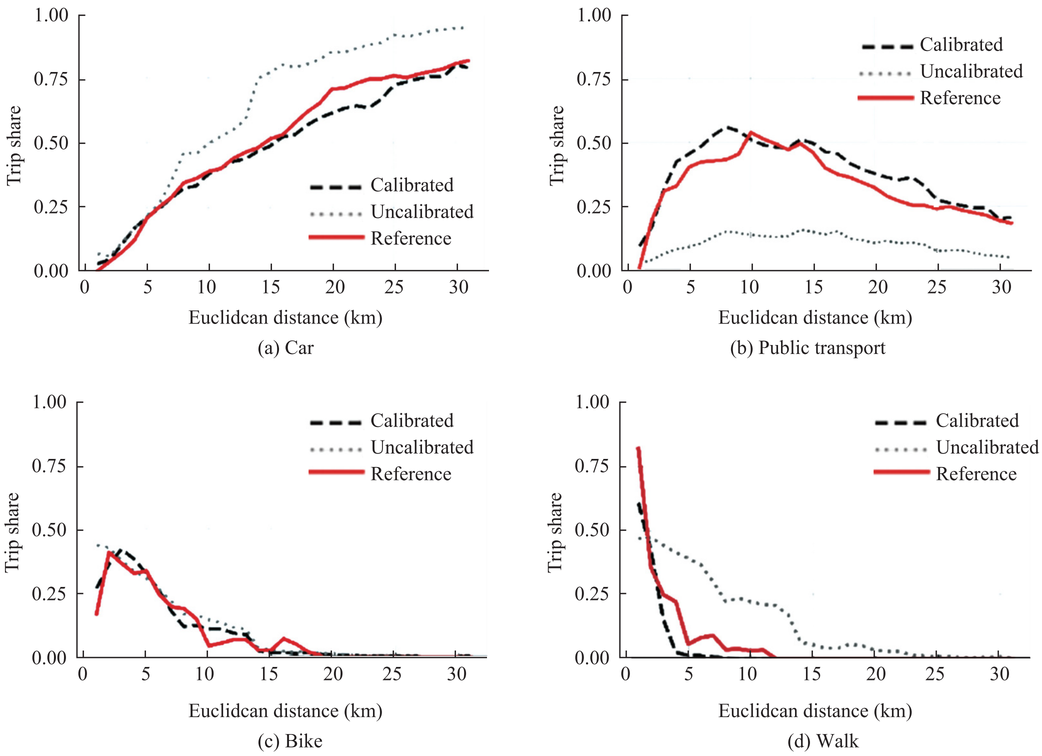

Fig. 4 Mode share calibration for travel distance

ers' mode choice decisions. Figure 5 illustrates the calculation of the total cost of a user's trip to study the relationship between cost and mode choice.

The results show that the cost of car trips is concentrated between 10 and 30 CNY. However, when the cost exceeds 50 CNY, the number of car trips decreases sig-

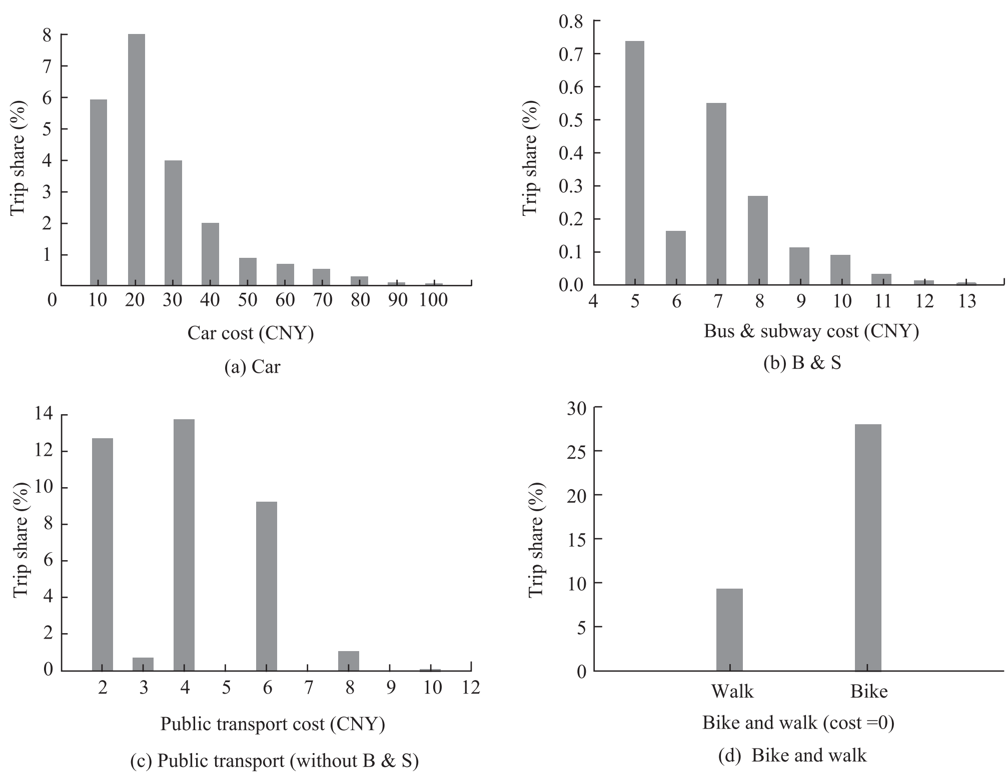

Fig. 5 Trip share for travel cost

nificantly, and the maximum cost observed is around 110 CNY. This suggests that there is a range of cost where car travel is preferred due to its better travel experience, but as the cost increases beyond a certain threshold, travelers are less inclined to choose the car. The comparison between car and public transport reveals that while car travel provides a better travel experience, it comes at a higher cost. This trade-off between comfort and cost influences the mode choice decisions of travelers in the study area.

The cumulative number of public transport trips with fares of 2, 4, 6 CNY amounts to 145 000 trips. When comparing these results to the data in the report[15], the average travel cost for subway trips is reported as 4.2 CNY, and for bus trips, it is 1.79 CNY. The simulated results are consistent with the report's data, demonstrating similar performance in terms of the average travel cost for public transport trips. Additionally, it is observed that public transport in the simulation model implements fixed fares that do not vary based on the travel distance. This is in line with real-world public transport systems in many places, where passengers pay a fixed fare regardless of how far they travel.

For non-motorized, bike trips are approximately 2.5 times more than walking. However, it is noted that the simulated percentage for bike trips is slightly higher than the actual data of 16.1%. This difference can be attributed to the assumption made in the model that non-motorized modes, do not incur any monetary charges or costs.

(2) Travel distance

The analysis of travel distance provides valuable insights into the distances covered by users of different modes, as presented in Figure 6.

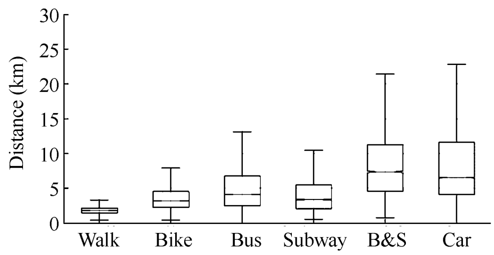

Fig. 6 Travel distance distribution

The average travel distances for each mode are as follows. The shortest average travel distance, approximately 2 km, indicates that walking is preferred for short-distance travel. The average travel distance for biking is around 4 km, making it another popular choice for short-distance trips. Both bus and subway modes have average travel distances within 5 km, suggesting that they are commonly used for relatively short trips as well. The highest average travel distances are observed for car and B&S, at approximately 7 km. This indicates that these modes are more commonly used for medium-distance travel.

To gain a more comprehensive understanding, the observation of the upper quartile is essential. The upper quartile provides insights into the longer travel distances. The upper quartile for walking is less than 5 km, most walking trips are short-distance. For bus, subway, and biking, it is around 10 km, suggesting that a significant portion of trips for these modes covers longer distances, up to 10 km. The upper quartile for car and B&S shows that they can cover distances exceeding 20 km, highlighting their suitability for longer trips.

Based on the report[15], it is observed that the transfer rate of the subway in the entire area of Shanghai is 1.75 boardings per trip, and the average distance covered by subway is 15.91 km. Since the study area is a subset of the entire Shanghai area, the transfer rate and average distance for subway trips in the study area would be lower than the reported city-wide values. Furthermore, the report[15] indicates that the average ride distance is 9.0 km for traditional taxi rides and 5.0 km for online car-hailing services. When compared to the simulated average travel distance of 7.0 km for car trips, the results are consistent and reasonable.

(3) Spatial accessibility

The spatial accessibility analysis, as visualized in Figure 7, provides valuable insights into the distribution of travel times reach the city center.

For car travel, the results indicate that the travel time to the city center is generally less than 30 min, and there is no significant clustering or dispersion, making it a well-accessible mode. The report[15] further supports this finding, showing that the average speed of the expressway network during rush hours allows for reaching a distance of 20 km within 30 min.

On the other hand, public transport accessibility exhibits a clear pattern along public transport routes, with a

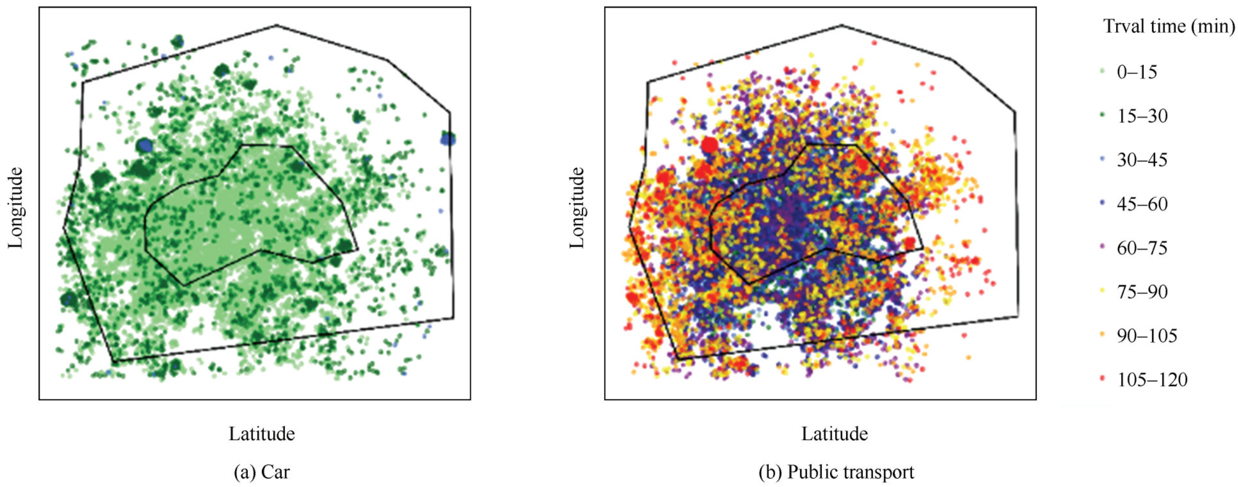

Fig. 7 Spatial accessibility for the car and public transport

tendency to spread outwards from the city center. The travel time along these routes is notably lower than in other areas, indicating that accessibility is heavily dependent on the presence and efficiency of the public transport infrastructure. The actual reported speeds of the subway (from 35 km/h to 40 km/h) and buses (13.5 km/h) during rush hours are lower, and the simulation results align with these values. The lower speeds of public transport, especially during rush hours, mean that longer travel times are required for the same distance as compared to car travel. This effect is especially prominent when there are no public transport stops near the departure place, leading to longer walking distances or the need to rely on other modes before boarding public transport.

5.2 System perspective

(1) Travel time

The analysis of the relationship between the starting and ending times for a trip for four modes, as depicted in Figure 8.

For car trips, it is evident that there are significant numbers of car trips during the morning peak hours (8:00-9:00), the noon peak hours (12:00-13:00), and the evening peak hours (17:00-19:00). These patterns align with the typical rush hours observed in reality, where many individuals use cars for their daily commute to and from work or school.

Public transport also exhibits similar peak hours, reflecting the usage patterns during the busiest times of the day. The similarity in peak hours between car and public transport further underscores the importance of providing efficient and reliable public transport services during these times to offer an attractive alternative to car travel.

Biking demonstrates a time distribution similar to that of cars. This may suggest that biking is perceived as a viable option for travel during these busy periods, especially for shorter distances or when traffic congestion is more prevalent.

Despite having the lowest number of trips, walking shows a time distribution similar to other modes, indicating that it is used throughout the day. Walking's flexible and adaptable allows it for short-distance travel and access to public transport stops.

(2) Trips and activity types

The analysis of activity types and their connections to trips, as shown in Figure 9, offers valuable insights into the patterns of travel behavior in relation to specific activities.

Home-Based Trips: Trips involving home as either the origin or destination (H-W, H-E, H-O, W-H, E-H, O-H) constitute a significant portion of all trips. These home-based trips exhibit noticeable morning and evening peaks, indicating the influence of daily routines such as commuting to work or school.

Commuting Trips: Within the home-based trips, commutes (H-W, W-H) stand out with distinct morning and evening rush hours, reflecting the regular movement of people to and from their workplaces or educational institutions. However, no noon peak is observed for commutes.

Non-Commuting Trips: Trips associated with non-

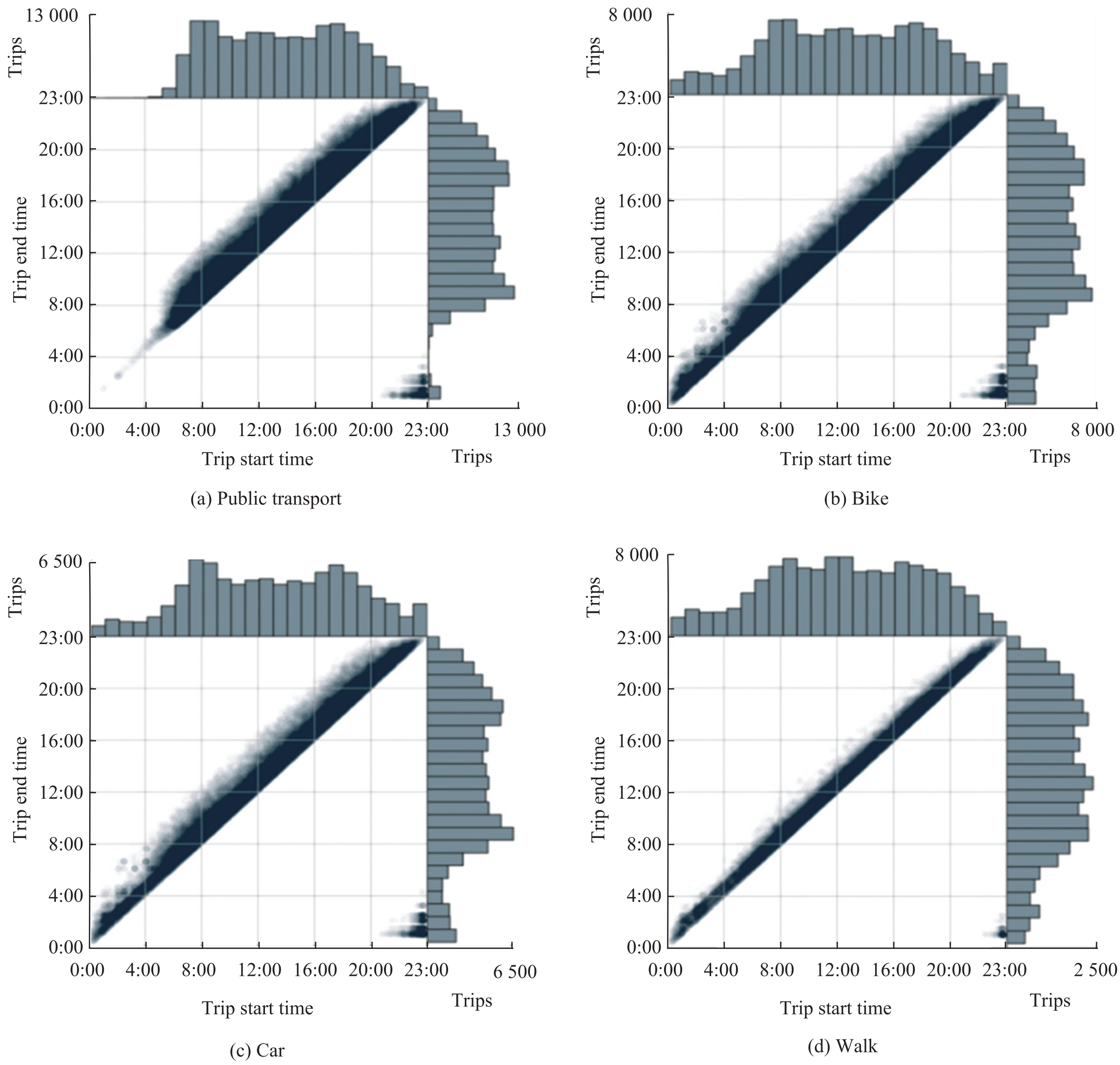

Fig. 8 Starting time and ending time distribution

commuting activities, such as shopping, entertainment, etc., show noon peak trips for the three primary modes: cars, public transport, and bikes. This suggests that entertainment activities like shopping and contribute to the increased travel demand during the midday period.

The alignment between the results and the reality validates the accuracy and reliability of the mode choice model in capturing the connections between trips and different activity types.

6 Conclusions

This study highlights the value of mobile phone signaling data as a valuable resource for generating travel demand for eqasim/MATSim. It sheds light on the multimodal travel behavior. The main conclusions obtained are as following.

(1) Feasibility of using mobile phone signaling data: this study demonstrates that using mobile phone signaling data is a feasible and effective approach to generate travel demand as input data for eqasim/MATSim simulation.

(2) User preference for public transport: individuals show a preference for choosing public transport over cars when the travel distance is comparable. Longer trips are efficiently covered by the Bus and Subway (B&S), which offers cheaper travel costs for users. However, the availability and coverage of public transport infrastructure significantly influence users' travel choices, as public transport options are limited to areas served by transportation services. In contrast, cars provide more flexibility and can avoid these restrictions.

(3) System perspective on travel patterns: the

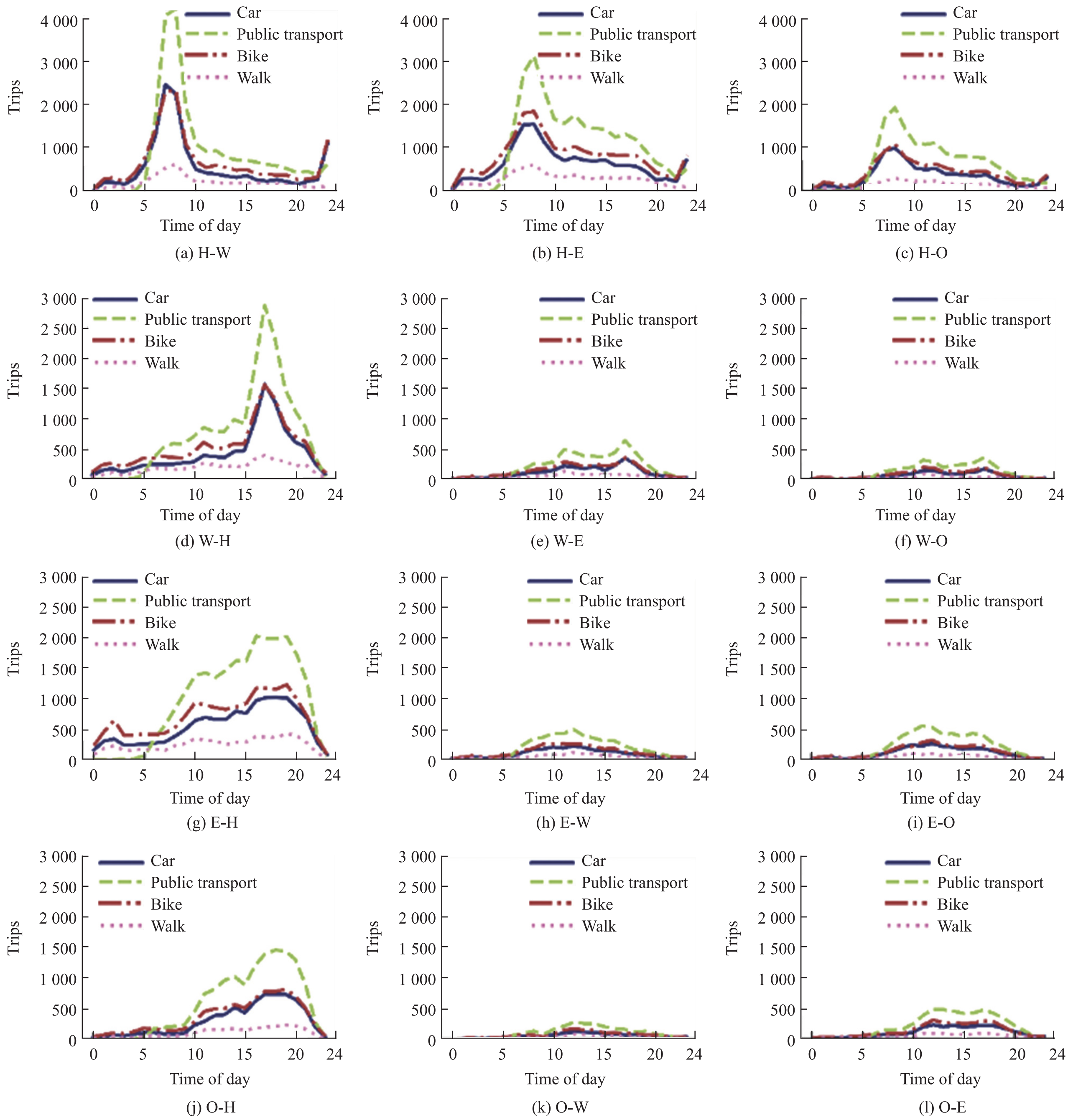

Fig. 9 The relationship between trips and activity types

highest percentage of trips are home-based, especially for commuting trips. The presence of significant morning and evening rush hours across all modes is primarily driven by the commuting behavior of individuals. These peak periods are a result of the regular movement of people to and from work or school, emphasizing the importance of efficient transportation solutions during these times.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

[1] HÖRL S, BECKER F, AXHAUSEN K W. Simulation of Price, Customer Behaviour and System Impact for a Cost-Covering Automated Taxi System in Zurich [J]. Transportation Research Part C: Emerging Technologies, 2021, 123: 102974.

[2] GAO K, SUN L, YANG Y, et al. Cumulative Prospect Theory Coupled with Multi-Attribute Decision Making for

Modeling Travel Behavior [J]. Transportation Research Part A: Policy and Practice, 2021, 148: 1-21.

[3] OKE J B, AKKINEPALLY A P, CHEN S, et al. Evaluating the Systemic Effects of Automated Mobility-on-Demand Services Via Large-Scale Agent-Based Simulation Of Auto-Dependent Prototype Cities [J]. Transportation Research Part A: Policy and Practice, 2020, 140: 98-126.

[4] AXHAUSEN K W, HORNI A, NAGEL K. The Multi-agent Transport Simulation MATSim [M]. London: Ubiquity Press, 2016: 9-21.

[5] BEHRISCH M, BIEKER L, ERDMANN J, et al. SUMO-simulation of Urban Mobility: An Overview [C]. IARIA. The Third International Conference on Advances in System Simulation. St. Maarten: ThinkMind. 2011

[6] BALAKRISHNA R, MORGAN D, SLAVIN H, et al. Large-scale Traffic Simulation Tools for Planning and Operations Management [J]. IFAC Proceedings, 2009, 42 (15), 117-122.

[7] HÖRL S, BALAC M. Introducing The Eqasim Pipeline: From Raw Data to Agent-Based Transport Simulation [J]. Procedia Computer Science, 2021, 184: 712-719.

[8] HÖRL S, BALAC M, AXHAUSEN K W. A First Look at Bridging Discrete Choice Modeling and Agent-based Microsimulation in MATSim [J]. Procedia Computer Science, 2018, 130: 900-907.

[9] DENG Y, ZHAO P. The Impact of New Metro on Travel Behavior: Panel Analysis Using Mobile Phone Data [J]. Transportation Research Part A: Policy and Practice, 2022, 162: 46-57.

[10] YANG C, ZHANG Y, ZHAN X, et al. Fusing Mobile Phone and Travel Survey Data to Model Urban Activity Dynamics [J]. Journal of Advanced Transportation, 2020, 2020 (6): 5321385. 1-5321385. 17.

[11] Open Street Map (OSM) [DB/OL]. [2018-11-1]. https: //www. openstreetmap. org/.

[12] General Transit Feed Specification (GTFS) [S/OL]. [2020-10-03]. https: //gtfs. org/.

[13] POLETTI F. Public Transit Mapping on Multi-modal Networks in MATSim [J]. Strasse Und Verkehr, 2017 (8): 22-25.

[14] Shanghai Municipal Development and Reform Commission. Shanghai Citizen Price Information Guide [EB/OL]. (2023-02-10) [2023-10-20] https: //www. shanghai. gov. cn/nw17239/20230210/388bc567f77f4886a0329-7221870f269. html. (in Chinese)

[15] Shanghai Comprehensive Transportation Annual Report 2020 [R/OL]. (2021-03-31) [2022-08-02]. https: //jtw. sh. gov. cn/gknb/index. html. (in Chinese)

[16] DUAN Q, YE X, LI J, et al. Empirical Modeling Analysis of Potential Commute Demand for Carsharing in Shanghai, China [J]. Sustainability, 2020, 12 (2): 620.