



# Exploring Differences in Daily Travel Patterns of Traditional and Ride-hailing Taxis Via Spatial-temporal OD Data: A Case Study of Jinan, China

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Received: 2 July 2025 / Accepted: 3 September 2025  
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## Abstract

The rapid proliferation of ride-hailing services has fundamentally reshaped urban mobility landscapes, challenging the operational paradigms of traditional taxi industries. While existing literature extensively explores the spatial and temporal patterns of ride-hailing, critical gaps persist in understanding the granular differences in daily travel behaviors between these two modes. This study addresses this gap through a data-driven analysis of traditional and ride-hailing taxis in Jinan, China, leveraging high-resolution spatial-temporal origin-destination (OD) datasets. By employing geostatistical modeling and efficiency metrics, we systematically quantify disparities in service coverage, trip distribution dynamics, and operational efficiency across six days of continuous observation. Results reveal that ride-hailing services not only double the trip volume of traditional taxis but also exhibit superior spatial adaptability, extending coverage to peripheral urban areas with a greater service radius. Temporal analysis reveals ride-hailing's optimized resource allocation, characterized by lower idle time during off-peak hours compared to traditional counterparts. Efficiency assessments indicate that traditional taxis contribute more to inefficient travel, often replacing non-motorized transport modes. This inefficient travel mainly comes from unplanned trips to the city center for leisure activities. These findings provide insights into integrated mobility systems that harness ride-hailing's spatial flexibility, supporting empirical study for more efficient urban transport planning.

**Keywords** Ride-hailing · Traditional Taxis · Spatial-temporal Patterns · OD Data Analytics · Urban Mobility Efficiency

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Published online: 17 September 2025

Springer

## Introduction

The disruptive emergence of platform-based ride-hailing services has irrevocably transformed urban transportation ecosystems over the past decade (Chan & Shaheen, 2012; Shi et al., 2021; Tu et al., 2019). Enabled by ubiquitous mobile connectivity and algorithmic dispatching, services like DiDi and Uber have achieved unprecedented market penetration (Jenn, 2020; Kondor et al., 2022; Zhao et al., 2023), with China's ride-hailing user base surpassing 437 million in 2022—a figure exceeding the combined populations of Germany and France (China Internet Network Information Centre, 2023; Tu et al., 2019). This tectonic Shift has precipitated a 32% decline in traditional taxi ridership across major Chinese cities between 2018 and 2023, as reported by the Ministry of Transport (Jin et al., 2018; Tirachini, 2020). While prior research extensively documents ride-hailing's environmental externalities and labor market impacts, critical knowledge gaps persist regarding its fundamental operational distinctions from conventional taxi services.

Existing scholarship predominantly adopts either macroeconomic perspectives evaluating ride-hailing's carbon footprint or microeconomic analyses of driver earnings (Cai et al., 2019; Gao et al., 2022; Zhu et al., 2018), leaving the spatial-temporal mechanics of daily trip patterns underexplored. Notably, absent are granular comparisons of how these competing services occupy urban space, respond to temporal demand fluctuations, and interface with public transport networks (Fang et al., 2024). This analytical void hinders evidence-based policymaking in cities undergoing mobility transitions, particularly in developing nations where ride-hailing growth outpaces the development of regulatory frameworks.

Our study bridges this gap through a data-intensive examination of Jinan, a representative Chinese metropolis undergoing rapid transport modernization. The primary research questions guiding this study are: (1) How do the temporal and spatial travel patterns of ride-hailing taxis differ from those of traditional taxis? (2) What are the key differences in trip efficiency between ride-hailing and traditional taxis? (3) How do the travel purposes of ride-hailing and traditional taxi trips differ, and what implications do these differences have for urban mobility?

By analyzing six days of high-resolution OD data encompassing 1.7 million taxi trips, we make three critical research contributions. First, we integrate a spatial efficiency index that quantifies service area utilization differences and identifies peak-period performance disparities. Second, we implement purpose-based trip categorization through machine learning-enabled POI analysis. This study aims to provide a comprehensive understanding of the operational differences between traditional and ride-hailing taxis, offering valuable insights into the development of more efficient and sustainable urban transportation systems. The subsequent sections detail our analytical framework, present empirical findings, and discuss implications for sustainable transport planning.

## Literature Review

Since the emergence of ride-hailing services, it has been recognized as a new way to promote green travel (Cai et al., 2019; Gao et al., 2022; Zhu et al., 2018). Ride-hailing platforms have integrated transportation resources, thanks to mobile internet support, eliminating information asymmetry (Naumov & Keith, 2023). This alleviated the significant supply-demand imbalance during peak periods and offered people high-quality, convenient travel options (Shaheen & Cohen, 2013). Hence, numerous studies have demonstrated that ride-hailing taxis conserve energy, enhance energy efficiency, reduce pollution, and are both sustainable and efficient (Cai et al., 2019; Jenn, 2020).

Early studies have predominantly focused on the environmental impacts of ride-hailing, with Cai et al. (2019) estimating a 12–15% reduction in per-trip emissions through vehicle sharing. Subsequent work by Tirachini (2020) challenged this optimism, demonstrating that ride-hailing's increased vehicle kilometers traveled could offset efficiency gains, a phenomenon known as the “rebound effect.” These contradictory findings underscore the need for granular operational comparisons.

Spatially, Vazifeh et al. (2018) pioneered fleet optimization models showing ride-hailing's theoretical potential to reduce taxi numbers by 30% through algorithmic dispatching. However, their simulation-based approach lacked empirical validation against real-world traditional taxi operations. Temporal analyses by Henao and Marshall (2019) revealed ride-hailing's 24% higher nighttime utilization in Denver, USA, but failed to consider Asian contexts with distinct commuting patterns.

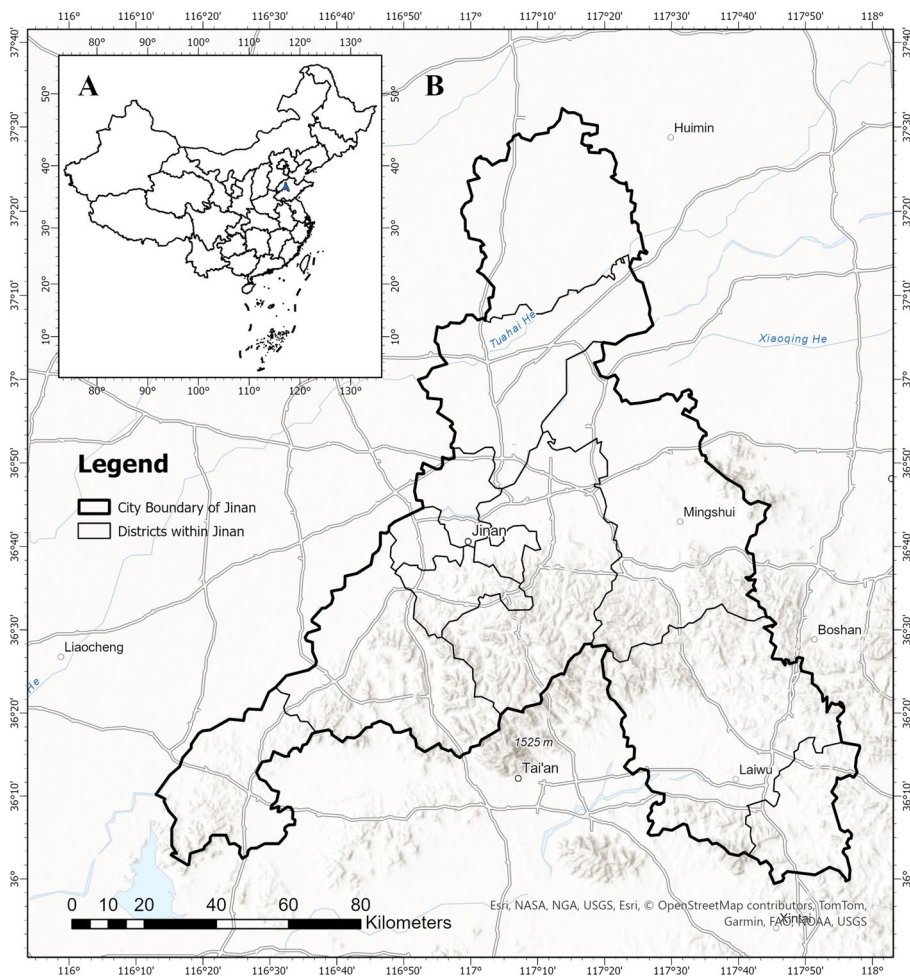
Methodologically, three gaps persist: First, existing studies rely on aggregated city-scale metrics (e.g., total trips, average speeds), neglecting fine-grained OD pattern analysis (Wang et al., 2024). Second, purpose-based trip classification remains rudimentary, with most research dichotomizing trips as “work” or “leisure” (Shi et al., 2021). Third, the assumed substitutability between taxi types lacks spatial-temporal evidence, particularly in rapidly urbanizing Asian cities.

Our study advances this discourse through three contributions: (1) High-resolution OD analysis at hourly granularity; (2) Efficiency benchmarking against multi-modal public transport alternatives; (3) Machine learning-enhanced trip purpose classification using LDA topic modeling. These provide new insights into how platform-driven systems are reshaping urban mobility patterns.

## Research Materials

### Research Area

The city of Jinan, located in Shandong Province, serves as an ideal case study for this research, as illustrated in Fig. 1. Renowned as the “Spring City” due to its numerous natural springs, Jinan is a rapidly developing metropolis with a population exceeding 9million. The city's urban layout features a compact old town surrounded by expanding residential and commercial districts, creating unique challenges and opportunities for mobility solutions. Jinan's transportation infrastructure includes a comprehensive



**Fig. 1** Geographical information of Jinan, China. **(A)** The geographical location of Jinan in China (the blue area). **(B)** The city boundary of Jinan and the districts within it

public transportation network; yet, the city still struggles with traffic congestion and pollution, common issues in many growing Chinese cities.

Ride-hailing services have emerged as a popular alternative to private car ownership and traditional taxis, offering residents more flexible and potentially more efficient travel options. The local government has also implemented policies aimed at reducing carbon emissions and promoting eco-friendly modes of transportation, such as electric vehicles and shared mobility platforms. These factors make Jinan an ideal setting for examining the differences in travel patterns between traditional taxis and ride-hailing services.

## Taxi Origin-destination (OD) Trip Data

The Municipal Bureau of Transport on Jinan Public Data Open Platform provides traditional taxi trajectories and ride-hailing taxi OD data (Municipal Bureau of Transport on the Jinan Public Data Open Platform). These two dataset records, as shown in Fig. 2, contain a wealth of information about each taxi trip, including device number, datetime, location, and taxi status, among others.

Due to data accessibility, the time dimension of the traditional taxi trajectory data spans six days from August 9 to 14, 2023, encompassing over 350 million raw GPS points in total. As shown in Fig. 2A, the original data format records the latitude and longitude of each taxi every 5 s via an on-board GPS device. Using the unique device ID of each taxi, the continuous GPS points were converted into OD records using the “taxigps\_to\_od” tool from the TransBigData package in Python (Yu & Yuan, 2022). This tool identifies an OD trip as the movement between two consecutive passenger pick-up and drop-off events, determined by changes in occupancy status.

To ensure data quality and comparability, we applied the same filtering rules to both datasets. For traditional taxis, we excluded trips outside the Jinan urban area and trips with durations shorter than 30s or longer than 8,000 s, which are considered abnormal. After cleaning, we obtained 548,959 valid OD trips in Jinan over six days.

| A | deviceno   | datetime            | lon        | lat       | speed | mileage | direction | state   | s_createtime                  |
|---|------------|---------------------|------------|-----------|-------|---------|-----------|---------|-------------------------------|
|   | 1000000046 | 2023-08-14 00:00:14 | 117.032227 | 36.660442 | 0.0   | 314102  | 272       | 1310976 | 2023/08/16 21:44:29.000000000 |
|   | 1000000046 | 2023-08-14 00:00:29 | 117.032227 | 36.660442 | 0.0   | 314102  | 272       | 1310976 | 2023/08/16 21:44:33.000000000 |
|   | 1000000046 | 2023-08-14 00:00:44 | 117.032227 | 36.660442 | 0.0   | 314102  | 272       | 1310976 | 2023/08/16 21:44:37.000000000 |
|   | 1000000046 | 2023-08-14 00:00:59 | 117.032227 | 36.660442 | 0.0   | 314102  | 272       | 1310976 | 2023/08/16 21:44:42.000000000 |
|   | 1000000046 | 2023-08-14 00:01:14 | 117.032227 | 36.660442 | 0.0   | 314102  | 272       | 1310976 | 2023/08/16 21:44:44.000000000 |
|   | ...        | ...                 | ...        | ...       | ...   | ...     | ...       | ...     | ...                           |

| B | VehicleNum | dep_time            | dep_longitude | dep_latitude | dest_time           | dest_longitude | dest_latitude | drive_time |
|---|------------|---------------------|---------------|--------------|---------------------|----------------|---------------|------------|
|   | 1000000046 | 2023-08-14 00:09:57 | 117.031883    | 36.660403    | 2023-08-14 00:52:36 | 117.085075     | 36.649835     | 2559.0     |
|   | 1000000046 | 2023-08-14 01:02:12 | 117.057245    | 36.654455    | 2023-08-14 01:06:06 | 117.031767     | 36.660322     | 234.0      |
|   | 1000000046 | 2023-08-14 01:47:36 | 117.010565    | 36.669088    | 2023-08-14 02:10:28 | 117.121558     | 36.625007     | 1372.0     |
|   | 1000000046 | 2023-08-14 03:43:41 | 117.031863    | 36.660267    | 2023-08-14 04:08:11 | 117.019315     | 36.662635     | 1470.0     |
|   | 1000000046 | 2023-08-14 04:28:49 | 117.010642    | 36.668827    | 2023-08-14 04:34:55 | 117.009347     | 36.686317     | 366.0      |
|   | ...        | ...                 | ...           | ...          | ...                 | ...            | ...           | ...        |

| C | vehicle_no   | wait_time | dep_longitude | dep_latitude | dep_time            | dest_longitude | dest_latitude | dest_time           | drive_mile | drive_time |
|---|--------------|-----------|---------------|--------------|---------------------|----------------|---------------|---------------------|------------|------------|
|   | 鲁A****09 ... | 0         | 117.529612    | 36.690069    | 2023-08-08 07:42:32 | 117.547274     | 36.685526     | 2023-08-08 07:46:29 | 2.00       | 180.0      |
|   | 鲁A****71 ... | 0         | 117.106923    | 36.872311    | 2023-08-08 07:42:21 | 117.094601     | 36.873782     | 2023-08-08 07:44:56 | 1.30       | 120.0      |
|   | 鲁A****03 ... | 0         | 117.125821    | 36.672990    | 2023-08-08 07:42:11 | 117.121691     | 36.665170     | 2023-08-08 07:45:42 | 1.60       | 180.0      |
|   | 鲁A****79 ... | 0         | 117.130663    | 36.942330    | 2023-08-08 07:42:07 | 117.145024     | 36.945078     | 2023-08-08 07:44:17 | 1.60       | 120.0      |
|   | 鲁A****89 ... | 0         | 117.182121    | 36.688300    | 2023-08-08 07:42:05 | 117.187971     | 36.709210     | 2023-08-08 07:45:59 | 2.90       | 180.0      |
|   | ...          | ...       | ...           | ...          | ...                 | ...            | ...           | ...                 | ...        | ...        |

**Fig. 2** Sample details of taxi origin-destination (OD) trip data. **(A)** The raw data of traditional taxis. **(B)** The post-processed data is in the OD format of traditional taxis. **(C)** The raw data of ride-hailing taxi OD data

As shown in Fig. 2B, each OD record contains the latitude–longitude coordinates of the origin and destination.

In contrast, the ride-hailing taxi data set (Fig. 2C) does not include continuous GPS traces; instead, it contains only the origin and destination coordinates, as well as timestamps, for each completed order, without intermediate trajectory points. The full dataset spans from 1 July to 9 August 2023 and comprises over 6.33 million OD records. To align with the traditional taxi study period, we extracted records from August 4 to 9, 2023. After removing spatial outliers and trips with abnormal durations (using the same criteria as above), we retained 1,147,764 valid OD records for analysis.

For OD flow analysis, the origin and destination coordinate of these two datasets were used directly in their original geographic location (latitude and longitude), without spatial aggregation into grids or administrative units. To ensure consistency and comparability between the two modes of transport, we selected the closest matching week within a similar seasonal and social context. While this period may not reflect all possible seasonal or behavioral variations, it corresponds to a typical summer week with no major disruptions (e.g., extreme weather events, major holidays), providing a relatively stable baseline for analyzing travel patterns under normal conditions.

### Public Transport Route Data

The route planning webservice of the API of some map companies can generate the shortest time between each OD pair based on the latitude and longitude for public transport trips (Chen et al., 2020). Based on comprehensive road network information in the actual city, combined with real-time road conditions, the AMap (Guide Map) API provides us with accurate route planning capabilities. This API web service can plan various types of travel routes that integrate all modes of public transportation (walking, cycling, bus, and metro) and return data, including routes, transit information, distance, duration, and travel cost. With the guidance of the API documents provided by the AMap, we crawled the ‘actual distance’ and ‘duration’ of the public transport route in Jinan under the fastest public transport interchange strategy mode to represent the optimal route for further comparison with taxi travel time. It is worth noting that this data crawling was conducted in November 2023, which is a relatively short time interval compared to the taxi OD data. Additionally, there have been no significant changes to the city’s transport infrastructure, and the calculated travel times remain reliable. However, due to changes in road/data/algorithm changes, there will likely be intervals where different results are returned based on API requests for the latitude and longitude of the same start and end points. This will have an impact on data accuracy to some extent, but the impact on the overall estimate of travel time can be negligible.

## Research Methods

The empirical foundation of this study rests upon three interconnected datasets capturing Jinan's taxi operations and urban infrastructure: Traditional taxi trajectory data, ride-hailing OD data, and public transport accessibility metrics. The resultant dataset enabled direct comparisons between taxi travel times and equivalent public transport durations, forming the basis for efficiency assessments.

Analytical methods progressed through three sequential phases: spatial-temporal pattern recognition and the use of space-time cubes to visualize trip distribution differences. Efficiency comparison utilized a normalized ratio of taxi travel time to optimal public transport duration. Travel purpose classification leveraged Latent Dirichlet Allocation (LDA) topic modeling on destination POIs, listings categorized into nine functional clusters.

### Spatial-temporal Analysis

To compare the spatial and temporal patterns of traditional and ride-hailing taxis, we analyzed the OD data using geostatistical methods. We aggregated the data into hourly and spatial intervals to identify trends in trip frequency, spatial distribution, and temporal dynamics. The analysis focused on the differences in service areas, trip density, and temporal variations between the two types of taxis.

### Efficiency Comparison

We defined trip efficiency as the ratio of the actual travel time by taxi to the optimal travel time by public transport. Trips with a ratio greater than 1 were considered inefficient, as they could potentially be replaced by public transport. We calculated the percentage of inefficient trips for both traditional and ride-hailing taxis to compare their overall efficiency. To be specific, in two categories:

1. Distance efficiency: Much research has proved that the maximum walking/cycling distance that people accept is 3 km (Macioszek et al., 2022; Tsunoda et al., 2021). Hence, if the travel distance from O to D is less than 3 km, which can be replaced by walking or cycling, the taxi trip is considered non-green.
2. Time efficiency: Travel time (including waiting and riding time) from O to D with a taxi is more than public transportation. The ways of using public transit include taking a combination of bus, metro, and walking. For each pair of OD trip records, i.e., if it meets the definition of any of the above inefficiency trips, it is recorded as 1. Otherwise, it is recorded as 0, as shown in Eq. (1).

$$y_i = (d_i < 3 \text{ km}) \text{ or } ((t_{wi} + t_{ri}) > t_{pi}) \quad (1)$$

where *or* denotes a logical operator. The  $d_i$  represents the actual distance of each trip  $i$ ,  $t_{wi}$  and  $t_{ri}$  means each trip's waiting time and riding time, respectively. And the  $t_{pi}$  is the travel time of the optimal public transport route between the  $i$  OD. Notably, wait times are publicly available information in ride-hailing taxi OD data.

Since the trajectory data of traditional taxis do not include the wait time information, each OD trip is distributed 30 s as the average wait time (Estrada et al., 2021; Wong et al., 2013; You et al., 2021).

## Travel Purpose Analysis

To fulfill the travel purposes of each OD record, the study identified the types of points of interest (POIs) located within 500 m of each travel destination using the reverse geocoding web service of the AMap API. Since the crawled POI types are diverse and inconsistently expressed, Latent Dirichlet Allocation (LDA) topic modeling was employed to cluster them into semantically coherent categories. To determine the optimal number of topics, we tested topic numbers from 5 to 11 and evaluated their performance using the  $c_v$  coherence score (Röder et al., 2015). The results were similar across this range (0.3928–0.4127), with the highest score occurring at six topics. Given that the differences were marginal, we selected nine topics for the final model to strike a balance between topic granularity and interpretability. This setting allowed us to obtain more detailed and meaningful POI categories without over-fragmenting the themes (Gu et al., 2024; Yu et al., 2022a, b). The nine categories were interpreted as follows: resident, shopping, business, leisure, culture, administration, transport, health services, and living services.

Using Bayesian networks in natural language processing, LDA operates as an unsupervised model that computes word frequencies within Points of Interest (POIs), treated as documents, gathered from each location. It then generates probabilistic topics using the bag-of-words approach. Broadly, LDA needs to establish two multinomial distributions to describe internal relationships, which are the topic-to-word matrix and the document-to-word matrix. In the topic-to-word one, each word within each generated topic can be assigned the probability indicating its significance (Callan & Association for Computing Machinery, 2003; Li, 2024; Yu et al., 2022a, b). By using words with high significance, we can infer the topic features corresponding to the POIs. The categories of POIs and the correspondence of the nine topics can be seen in Table 1. Based on this, we can broadly understand the purpose of each taxi trip and further analyze which goals are causing more inefficient travel.

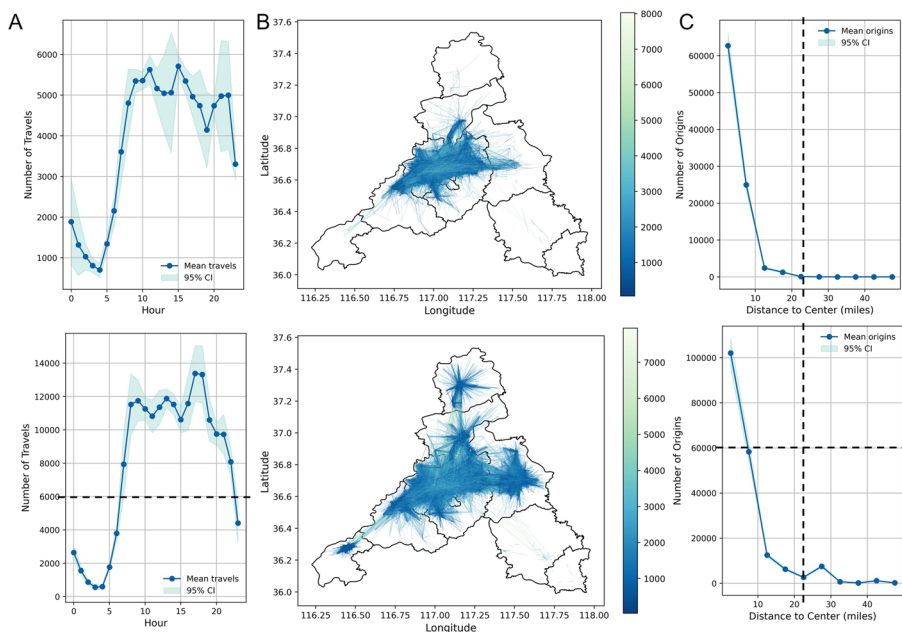
## Results

### Spatial-temporal Patterns Variation

Figure 3A illustrates the temporal distribution of OD trips for traditional taxis and ride-hailing taxis across 24 h. Traditional taxis exhibit a strong bimodal pattern, with distinct morning and evening peaks. The number of trips starts at a relatively low level around midnight, with fewer than 5,000 trips per hour. Between 5:00 and 7:00 AM, the number of trips rises sharply, reaching approximately 25,000 trips per hour. The morning peak occurs between 7:00 and 10:00 AM, with a maximum of around 33,000 trips per hour. A second peak is observed in the afternoon, between 1:00 and 3:00 PM, with trip volume exceeding 30,000 trips per hour before decreasing sharply

**Table 1** Reference correspondence between nine topics and pois of destination

| Topics         | POIs                                                                             |
|----------------|----------------------------------------------------------------------------------|
| Resident       | Residential community, residential building, dormitory, cottage, etc.            |
| Shopping       | Mall, shopping center, electrical mall, brand store, etc.                        |
| Business       | Office, business building, company, factory, etc.                                |
| Leisure        | Scenic spots, tourist attractions, sports centers, parks, squares, cinemas, etc. |
| Culture        | Schools, science museums, theatres, educational institutions, etc.               |
| Administration | Government agencies, police stations, social organizations, etc.                 |
| Transport      | Metro stations, bus stations, railway stations, airports, etc.                   |
| Health service | Hospitals, healthcare, clinics, nursing homes, etc.                              |
| Living service | Food market, kiosk, furniture repair, bank, etc.                                 |



**Fig. 3** Spatial-temporal patterns of traditional (up) taxi and ride-hailing (down) taxis' OD trip data in Jinan. **(A)** Temporal variation of taxi trips per hour. **(B)** Spatial distribution of the whole taxi OD trip data. **(C)** The relationship between the distance to the city center and the corresponding number of the origin of each trip. **Notes:** Based on the urban context of Jinan, the city center was considered as Quancheng Square in this study, located at 117.022194°E, 36.661612°N. We calculated the straight-line distance between the origin of each trip and Quancheng Square to represent the distance to the center of the city

after 9:00 PM. After 9:00 PM, trips decline gradually but remains above 20,000 trips per hour throughout the midday period.

In contrast, ride-hailing taxis (bottom plot) exhibit significantly higher trip volumes, with a more stable distribution across the day. The number of trips is lower than 10,000 per hour before 5:00 AM but increases rapidly afterward. Between 6:00 and 9:00 AM, the number of trips rises sharply, reaching around 70,000 trips per hour at its peak, which is nearly double that of traditional taxis. Unlike traditional taxis, the ride-hailing service maintains a high trip volume throughout the day, with hourly trips consistently above 45,000. The evening peak, occurring between 3:00 and 7:00 PM, reaches approximately 80,000 trips per hour, surpassing the morning peak. The relatively stable distribution of ride-hailing trips throughout the day suggests that they serve not only commuting but also other travel purposes, which are not constrained by rush-hour demand.

The spatial distribution of OD trips, shown in Fig. 3B, highlights the geographic extent of taxi services. Traditional taxis (top map) demonstrate a high concentration of travel activity within the central urban area of Jinan, particularly in the downtown region near 117.0°E longitude and 36.7°N latitude. The highest trip densities, represented by darker blue colors, are confined to the core city area, with relatively sparse coverage in suburban and rural regions. The spatial patterns suggest that traditional taxi services primarily cater to short-distance urban travel within the central business district (CBD) and nearby residential zones. The trip density drops significantly beyond approximately 10 km from the city center, indicating that traditional taxis rarely serve long-distance inter-district trips.

In contrast, the ride-hailing OD trip map (Fig. 3B, bottom map) exhibits a much broader spatial distribution. While the central area still maintains a high travel density, ride-hailing trips are extending further into suburban and even peripheral rural areas. Multiple hotspots outside the downtown core, particularly in the southern and north-eastern parts of the city, suggest that ride-hailing taxis serve a wider range of origins and destinations compared to traditional taxis. The presence of strong inter-regional connectivity highlights the flexibility and accessibility of ride-hailing services. The trip density remains significant beyond 20 km from the city center, demonstrating the ability of ride-hailing platforms to facilitate long-distance trips that traditional taxis do not frequently cover.

Figure 3C quantifies the relationship between the number of trips and their distance from the city center. For traditional taxis (top plot), the number of trip origins is heavily concentrated within 5 km of the city center, where over 350,000 trip origins are recorded. As the distance increases, the number of trips declines sharply, with fewer than 50,000 origins between 10 and 15 km and near-zero origins beyond 20 km. This steep decline indicates that traditional taxis predominantly operate within central urban areas, rarely picking up passengers from suburban or rural locations. The vertical dashed line at approximately 20 km marks a threshold beyond which traditional taxi services become negligible.

Conversely, the ride-hailing trip origin distribution (Fig. 3C, bottom plot) shows a more gradual decline. The highest concentration of trip origins remains within 5 km of the city center, with over 600,000 trips, nearly twice the volume recorded for traditional taxis. However, the decline beyond this distance is much less steep. Between

5 and 10 km, the number of ride-hailing trip origins still exceeds 100,000, and even beyond 20 km, the number of trip origins remains above 30,000. This distribution indicates that ride-hailing services are significantly more accessible to residents living in suburban and rural areas. The presence of a flatter decay curve in ride-hailing trip origins highlights its role in bridging mobility gaps for peripheral communities. Unlike traditional taxis, which primarily operate in densely populated downtown areas, ride-hailing platforms expand their service coverage to lower-density regions, enabling greater mobility for users outside the urban core.

A comparative analysis of the two services reveals substantial differences in trip volume, spatial reach, and travel patterns. Ride-hailing taxis account for more than 1.5 times the total trip volume of traditional taxis, with a peak of 80,000 trips per hour compared to 35,000 visits per hour for traditional taxis. The spatial coverage of ride-hailing services extends beyond 20 km from the city center, while traditional taxis primarily operate within 10 km. Moreover, ride-hailing services maintain consistently high trip volume throughout the day, whereas traditional taxis exhibit more pronounced rush-hour peaks.

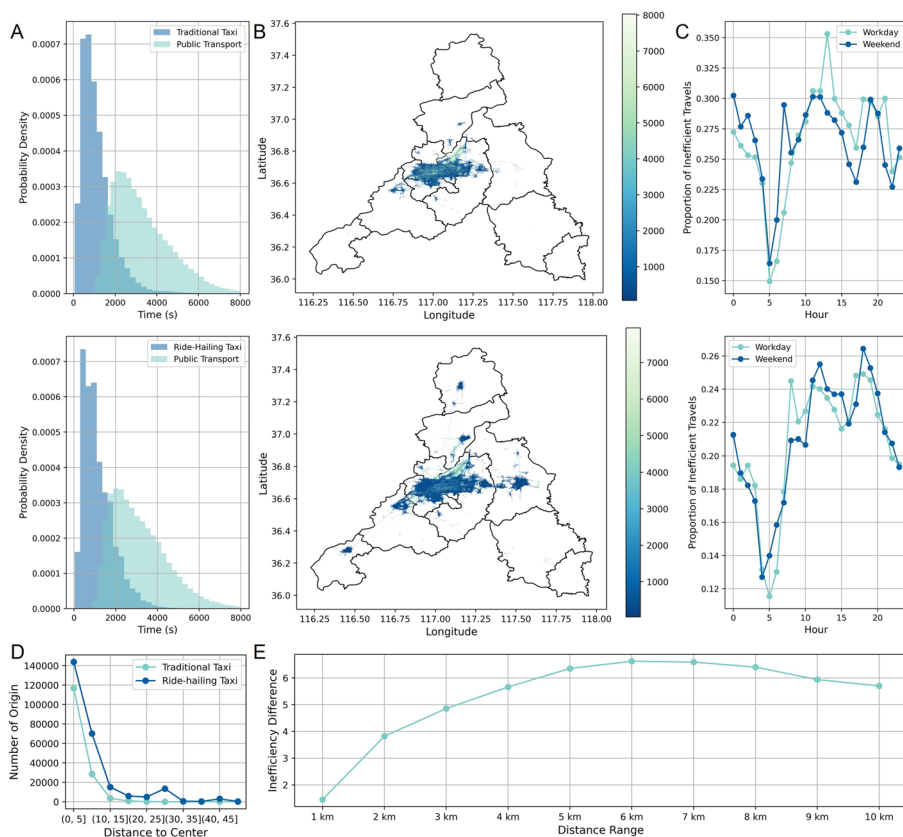
From an accessibility perspective, ride-hailing platforms significantly enhance mobility for suburban residents. The number of trip origins beyond 10 km for ride-hailing taxis is more than five times higher than that of traditional taxis. Additionally, the spatial heatmaps indicate that ride-hailing services generate a more distributed travel pattern, supporting both intra-urban and inter-district trips.

## Operational Efficiency Comparison

### Travel time Comparison

Figure 4 A presents the probability density of travel time distributions for traditional taxis and ride-hailing taxis compared to public transport. In both cases, taxi-based travel shows a significantly shorter duration than public transport. For traditional taxis, the majority of trips are concentrated within 30–2000 s (0.5–33.3 min), with a peak around 600–800 s (10–13.3 min). The probability density sharply declines beyond 2000 s, indicating that most traditional taxi trips are relatively short in duration. In contrast, public transport trips show a broader distribution, with a larger proportion extending beyond 3000 s (50 min), suggesting that public transport serves longer trips more effectively.

A similar trend is observed for ride-hailing taxis, with most trips falling within the 30–2500 s range. However, compared to traditional taxis, ride-hailing services exhibit a slightly more dispersed distribution, with a higher probability density beyond 2000 s. This suggests that ride-hailing services cater to a wider range of trip lengths, possibly due to their more flexible availability and dynamic pricing strategies. The overlap between the two distributions indicates that while both modes primarily serve short-distance trips, ride-hailing taxis are more frequently used for longer trips than traditional taxis.



**Fig. 4** Spatial-temporal patterns of traditional taxis and ride-hailing taxis' efficiency travel in Jinan. **(A)** Comparing the time distribution between travels by traditional (up) taxis or ride-hailing (down) taxis and travel by public transport. **(B)** Spatial distribution of inefficient travel. **(C)** The percentage of inefficient travel among all trips per hour, on both workdays and weekends. **(D)** The relationship between the distance to the city center and the corresponding origin number of each inefficient trip. **(E)** The relationship between the short non-motorized travel distance and the inefficiency difference between traditional and ride-hailing taxis.

### Travel Routes Comparison

Figure 4B illustrates the spatial distribution of inefficient trips, characterized by travel routes that could be replaced with more sustainable alternatives. The heatmaps indicate that the highest density of such trips is concentrated in the urban core of Jinan, particularly around central business districts and major transit hubs. The color gradient, ranging from blue (low density) to green (high density), highlights areas with excessively inefficient taxi-based trips.

For traditional taxis, the highest concentration is observed within the downtown area, spanning approximately 116.85°E to 117.10°E longitude and 36.60°N to 36.75°N latitude. The intensity decreases as we move towards the periphery, indicating that inefficient taxi travel is primarily a phenomenon of urban areas.

Ride-hailing taxis exhibit a broader spatial footprint, with inefficient trips extending further into suburban regions compared to traditional taxis. Notably, ride-hailing services generate a significant number of trips in outer urban districts, particularly between 116.75°E and 117.15°E longitude. This suggests that ride-hailing taxis may be contributing to increased vehicle kilometers traveled in areas with lower public transport accessibility, thereby reducing potential environmental benefits.

Figure 4D examines how the origin points of inefficient trips are distributed based on their distance from the city center. For traditional taxis, the number of inefficient trips sharply declines as the distance increases. In the 0–5 km ranges from the city center, the number of trips is highest, reaching nearly 120,000 visits. This value rapidly drops to below 30,000 trips in the 5–10 km range and becomes negligible beyond 30 km.

Ride-hailing taxis follow a similar trend, but with a slightly longer distribution. The highest number of inefficient trips remains within the 0–5 km range, but with a somewhat higher count (~145,000 visits). The decline beyond 10 km is more gradual compared to traditional taxis, with ride-hailing trips maintaining a non-trivial presence even in the 20–30 km range. This indicates that ride-hailing taxis contribute more to inefficient long-distance travel compared to traditional taxis, reinforcing the observation that they are more widely used in suburban areas.

### Temporal Variation of Travel (Workday Vs. Weekend)

Figure 4C depicts the proportion of inefficient trips as a function of time across workdays and weekends. For both taxi types, inefficiency fluctuates throughout the day, with distinct peak and off-peak periods. On workdays, traditional taxis exhibit an inefficiency proportion ranging from 0.15 to 0.36, with the highest peaks occurring between 10:00 AM–3:00 PM. These peaks align with morning and evening rush hours, suggesting that a substantial portion of taxi trips during these times could be replaced by more efficient transit options.

On weekends, the inefficiency pattern for traditional taxis shifts slightly, with fluctuations occurring between 0.17 and 0.31. The peak inefficiency occurs later in the morning (around 10:00 AM) and remains relatively high until the early evening, meaning that leisure-based travel contributes to inefficient taxi usage. Ride-hailing taxis display a slightly different pattern. On workdays, inefficiency fluctuates between 0.11 and 0.25, with a pronounced midday peak around 5:00–7:00 PM. At weekends, inefficiency remains relatively high throughout the day, peaking at 0.27 around 6:30 PM, reflecting a greater reliance on ride-hailing compared to workdays.

### Short Non-Motorized Travel Distances on Inefficiency

Figure 4E evaluates the inefficiency difference between traditional and ride-hailing taxis based on short non-motorized travel distances. As distance increases, inefficiency rises, peaking at approximately 6 km, with a difference of about 7. This suggests that ride-hailing services are particularly substituting short-distance trips that could be made by walking or cycling, exacerbating urban congestion and emissions.

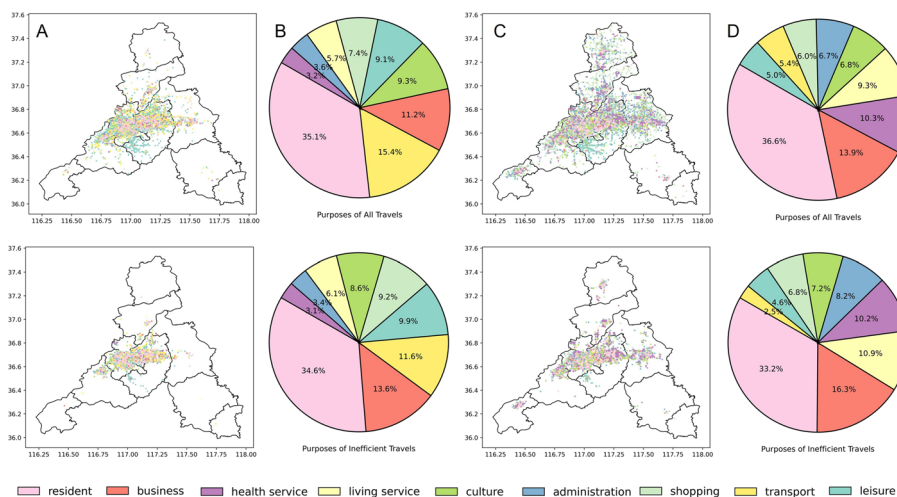
Beyond 6 km, the inefficiency difference gradually declines. At 10 km, the difference is approximately 5.8, indicating that the inefficiency of ride-hailing taxis relative to traditional taxis becomes less pronounced at longer distances. This pattern suggests that ride-hailing taxis compete with active transport for shorter trips rather than providing a distinct advantage over traditional taxis for longer journeys.

### Travel Purpose Differentiation

Figure 5 provides a detailed breakdown of the trip purposes for both traditional taxis and ride-hailing vehicles. For traditional taxis, the leading purpose is “residential” travel, accounting for 35.1% of all trips. “Business” trips follow with a share of 15.4%, and “transportation interchange” and “shopping” occupy 11.2% and 9.3%, respectively. For other travel purposes, such as “administration,” “culture,” “living service,” and “health service,” each contributes less than 10% of the total.

Ride-hailing services exhibit a slightly different structure. “Residential” travel accounts for a significantly higher proportion at 36.6%, confirming its strong role in daily commutes. However, the proportion of “business” trips drops slightly to 13.9%. More interestingly, there is a noticeable increase in the share of travel related to “health service” (10.3%), “living service” (9.3%), and “shopping” (6.8%). This suggests that ride-hailing is more frequently used for diverse functional activities beyond commuting, particularly those related to personal well-being and daily errands.

This structural difference indicates that ride-hailing services are used for a broader array of trip purposes. Traditional taxis serve more professional and central busi-



**Fig. 5** Different patterns of the whole (above) and inefficient (below) taxi travel purposes in Jinan. **(A)** Comparing the spatial patterns of destinations for different travel purposes of traditional taxi travel. **(B)** Comparing the percentage of travel purposes of traditional taxi travel. **(C)** Comparing the spatial patterns of destinations for different travel purposes of ride-hailing taxi travels. **(D)** Comparing the percentage of travel purposes of ride-hailing taxi travels

ness district-oriented purposes, whereas ride-hailing accommodates a wider variety of needs, including more individualized and discretionary activities.

The lower panels of Fig. 5B and D show the proportion of inefficient trips, those not directly related to work, essential services, or transport interchanges. For traditional taxis, inefficient trips are still dominated by “residential” purposes (34.6%), followed by “business” (13.6%), “transport” (11.6%), and “leisure” (9.9%). The shares for “shopping,” “culture,” “living service,” “administration,” and “health service” are 9.2%, 8.6%, 6.1%, 3.4%, and 3.1%, respectively.

In comparison, ride-hailing’s inefficient trips demonstrate a more diversified structure. “Residential” and “business” still lead with 33.2% and 16.3%, but the share of “living service” increases to 10.9%, “health service” rises to 10.2%, and “culture” jumps to 7.2%. Notably, “administration” reaches 8.2%, significantly higher than the 3.4% recorded for traditional taxis. The proportion of “transport interchange” among inefficient ride-hailing trips drops to just 2.5%, possibly due to reduced dependency on ride-hailing for public transit connections in non-essential scenarios.

These differences suggest that ride-hailing services are increasingly preferred for more planned or essential trips, particularly those related to living services, administrative tasks, and healthcare. This may be due to the convenience, reliability, and on-demand accessibility of ride-hailing platforms, which provide a more comfortable and predictable travel experience than street-hailed taxis.

Cross-analysis between trip purposes and their spatial destinations further emphasizes the service distinctions between the two modes. Traditional taxis show a strong cooperation between “business,” “transportation interchange,” and central business districts. Their trips are heavily clustered in areas with office buildings, train stations, and public service hubs. This reflects the traditional taxi’s role in serving structured, routine, and predictable travel needs.

Ride-hailing trips, on the other hand, are more spatially diverse across all trips. Destinations for “culture,” “leisure,” and “living services” are dispersed toward suburban areas such as the Olympic Sports Center in the east and the southern mountain attractions. These patterns suggest that ride-hailing serves a more flexible and comprehensive set of travel demands, playing a supplementary role in areas not well served by public or traditional transportation systems.

Moreover, administrative and medical trip destinations are more evenly distributed among ride-hailing users. Locations such as the Jinan Municipal Government offices and the Shandong Provincial Hospital East Campus are among the most frequent destinations. This suggests that ride-hailing services better support travel to specialized or less centrally located facilities.

## Discussion

Based on the conventional use of geostatistics and topic modeling, this study furthers the understanding of traditional and ride-hailing taxi modes by integrating a high spatial-temporal resolution OD dataset with an efficiency index, multi-scale temporal performance analysis, and machine learning-enabled trip purpose classification. These methodological innovations enable a more granular, performance-oriented,

and transferable understanding of operational differences, thereby offering actionable insights for sustainable urban transport policy.

Based on the preliminary insights attained from the research months, our context-specific findings challenge binary narratives that frame ride-hailing and traditional taxis as direct competitors, instead revealing their complementary roles in urban mobility ecosystems. Traditional taxis remain indispensable for predictable, center-oriented business travel, where fixed routes and immediate availability align with the needs of commuters. Ride-hailing, by contrast, excels in servicing fluid demand across expanding urban peripheries, leveraging algorithmic dispatching to optimize resource allocation in real-time. This duality suggests that policymakers can adopt nuanced strategies to harness the strengths of both modes while mitigating systemic inefficiencies.

Three policy implications emerge from this analysis. First, appropriate subsidies could incentivize taxi services to prioritize suburban growth corridors, counteracting market forces that concentrate drivers in profitable downtown areas. For instance, tiered fare multipliers for trips originating in underserved zones, coupled with reduced platform commissions, could enhance service reliability in peripheral regions. Second, traditional taxi fleets could optimize availability through dynamic permitting systems tied to demand patterns. By issuing time-limited permits for business districts during peak hours, cities could reduce oversupply while maintaining service quality for structured commutes. Third, integrated mobility platforms are better suited to formalize ride-hailing's role in accessing essential services. Partnerships with suburban hospitals and universities could establish dedicated pickup zones, ensuring reliable transportation for patients and students. Although these policy recommendations are now presented as preliminary insights that should be validated with more comprehensive cases in future work, they still offer valuable guidance for governments and local planners.

The study also highlights ride-hailing's potential to contribute to sustainability goals. The observed reduction in inefficient trips, while modest at the municipal scale, assumes significance when extrapolated to China's 4.3 billion annual ride-hailing trips. When combined with vehicle electrification, which has already been adopted by 38% of DiDi's fleet in Jinan, the carbon savings could be amplified substantially. However, sustainability gains risk being undermined by induced demand; the convenience of ride-hailing may encourage inefficient short-distance trips. Policymakers could therefore balance accessibility enhancements with demand management, such as congestion pricing or trip-pooling incentives.

The limitations of this study should be acknowledged and invite future researchers to explore potential directions. The six-day observation period may obscure weekly or seasonal variations, particularly in leisure travel patterns. Additionally, the lack of precise fleet size information for traditional taxis and ride-hailing vehicles, as car identifiers were not available, limits our ability to control for supply-side differences. Regarding the identification of trip purposes, the LDA-based POI classification is inherently constrained by the granularity and semantic ambiguity of the underlying

POI data. Certain categories, such as residential, are broad and may not accurately reflect the actual trip purpose—e.g., not all trips ending in residential areas are necessarily “home trips.” The reliability of the inferred purposes, therefore, depends on both the representativeness of the POI dataset and the interpretability of topic clusters. Future research could integrate higher-resolution land-use datasets, mobile phone signaling, or survey data to validate and refine topic interpretations.

Moreover, multi-city comparisons could assess the generalizability of the findings, and exploring the impact of driver incentive structures on service patterns would offer additional insights. Longitudinal tracking of mobility behaviors after policy interventions—such as subsidy rollouts or electrification mandates—would further clarify the long-term sustainability impacts of ride-hailing. Taken together, the study reveals that ride-hailing is an important enabler in more efficient urban transport systems. By quantifying operational divergences through high-resolution OD data, we provide a replicable framework for cities navigating mobility transitions.

## Conclusions

This comprehensive spatial-temporal analysis of traditional and ride-hailing taxi operations in Jinan, China, yields critical insights into the evolving dynamics of urban mobility systems. Through the examination of millions of OD records and integration of the efficiency metrics, three main findings emerge as the cornerstone of this research:

- Traditional taxis in Jinan primarily serve urban commuters with concentrated travel activity in the city center and a strong dependence on rush-hour demand. In contrast, ride-hailing services exhibit higher trip volume, broader spatial coverage, and greater accessibility for suburban and long-distance travelers.
- Temporal analysis reveals that traditional taxis experience peak inefficiency during weekday rush hours, whereas ride-hailing taxis see higher inefficiency during midday and weekends. Moreover, traditional taxis contribute more to inefficient short-distance travel, often replacing non-motorized transport modes.
- Reading the travel purposes, ride-hailing services are preferred for planned or essential travel compared to traditional ones, particularly for living services, administrative tasks, and healthcare. This can be attributed to the reliability and on-demand nature of ride-hailing platforms.

These findings highlight the need for policy interventions to promote sustainable transport alternatives, particularly for short-distance urban travel. Encouraging active transportation modes and enhancing public transit accessibility in suburban areas could mitigate the environmental impacts associated with inefficient taxi travel.

**Author Contributions** X.G. processed data and prepared Figs. 1, 2, 3, 4 and 5. All authors wrote the main manuscript text and reviewed the manuscript.

**Funding** Open access funding provided by The Hong Kong Polytechnic University. The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

**Data Availability** The data supporting this study's findings are available and downloaded from the Municipal Bureau of Transport on the Jinan Public Data Open Platform (Municipal Bureau of Transport on the Jinan Public Data Open Platform). The availability of this data is restricted and therefore not publicly available. Data will be available from the authors upon reasonable request and with permission of the Municipal Bureau of Transport on the Jinan Public Data Open Platform.

## Declarations

**Competing Interests** The authors declare no competing interests.

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