

# **Choosing My Own Path: Revealing Differences in Route Choice Preferences across Long-Haul, Medium-Haul, and Short-Haul Trucking**

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2 **Preferences across Long-Haul, Medium-Haul, and Short-Haul**  
3 **Trucking**

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# 1 **Abstract**

2 The rapid growth in e-commerce activities and the constant specialization of industries have  
3 aroused an unparalleled demand for trucking in urban areas, leading to growing concern over its  
4 interference to the transportation system. Understanding truck route choice preferences across  
5 long-haul, medium-haul, and short-haul trips can offer insights for designing the truck route  
6 network tailored to specific freight demand types, so as to effectively reduce their interference to  
7 passenger transportation. However, limited research has been conducted to explore the  
8 heterogeneity or similarity of route choice preferences across those freight demand types. This  
9 study utilizes the Path Size Logit Model to explore the characteristics of preferred route across  
10 long-haul, medium-haul, and short-haul trips, and reveal the underlying route choice mechanism  
11 behind enormous trucking activities. By employing truck GPS data from China, we find that (1)  
12 although the characteristics of preferred routes vary across long-haul, medium-haul, and short-  
13 haul trips, those trips collectively reflect full consideration of travel efficiency, safety, and  
14 reliability; (2) all these freight demand types incline to the routes with shortest travel distances  
15 instead of those with shortest travel time, while short-haul trips exhibit the highest sensitivity to  
16 travel distance; (3) drivers in both long-haul and medium-haul trips favor routes that combine  
17 motorways and sub-arterial roads, while long-haul trips present higher sensitivity; (4) drivers in  
18 short-haul trips show preferences for routes featuring fewer turns, and sub-arterial roads given  
19 last-mile delivery demand. Finally, we propose suggestions for designing urban truck route  
20 network to accommodate diverse freight demand in high-density urban areas with limited road  
21 resources.

22

23 *Keywords:* truck route choice, GPS data, path size logit model, truck route network

# 1 **1. Introduction**

2 The rapid growth of e-commerce and the constant specialization of industries have raised an  
3 unparalleled rise in demand for goods delivery (Giuliano et al., 2016; Yang et al., 2021b). Given  
4 the convenience of road transportation, it remains the primary mode for goods delivery in urban  
5 areas, leading to a significant and persistent increase in truck travel on urban roads (Holeczek,  
6 2019; Shoman et al., 2023). This considerable reliance on road transportation brings a series of  
7 negative externalities, including severe traffic congestion, traffic accidents, air pollution, and  
8 road damage (Ma et al., 2016; Sharma et al., 2022; Yang et al., 2021a; Yu et al., 2023; Yu et al.,  
9 2024; Yuan and Wang, 2021). Investigating truck route choice preferences can provide the  
10 theory basis for constructing the truck route network, thereby enabling effective management of  
11 truck traffic flows, and mitigating their impact on the urban transportation system (Nadi et al.,  
12 2022; Qin et al., 2023; Ramirez-Rios et al., 2023; Tao and Zhu, 2020).

13 Truck route choice preferences exhibit heterogeneity across long-haul, medium-haul, and  
14 short-haul trips (Luong et al., 2018; Toledo et al., 2020). Specifically, variations in travel  
15 distance often entail differences in delivery requirements, encompassing the value of goods,  
16 delivery timeliness, and costs (Feng et al., 2013; Kinjarapu et al., 2022; Yang et al., 2022a).  
17 These discrepancies significantly impact the sensitivity of route decision-makers to route  
18 economics, safety, and reliability, thereby influencing the outcomes of route choice (Rowell et  
19 al., 2014; Wang and Zhang, 2017; Wang and Goodchild, 2014). Examining this heterogeneity  
20 aids in developing a more tailored truck route network, which not only ensures truck operational  
21 efficiency but also minimizes its impact on the urban traffic system.

22 Previous studies have employed questionnaire data or large-scale GPS data to analyze truck  
23 route choice behavior, with some specifically investigating route preferences in different travel

1 scenarios, such as long-haul, intercity trips, peak and off-peak travel (Feng et al., 2013; Luong et  
2 al., 2018; Sharma et al., 2022; Toledo et al., 2020; Wang and Goodchild, 2014). However, there  
3 is limited empirical research comparing the truck route preferences across varying freight  
4 demand in travel distance. On the other hand, even though several studies have delved into route  
5 choice preferences across long-haul, medium-haul, and short-haul travel scenarios, the  
6 predominant focus has been on passenger transport (Deng et al., 2020; Jou and Yeh, 2013;  
7 Yamamoto et al., 2018). Given the factors such as weight and/or size of the truck, driving  
8 restriction, and convenience for goods loading and unloading, the findings regarding route choice  
9 preferences in passenger transport may not directly apply to truck travel. Therefore, further  
10 investigation is warranted into the similarities or disparities in truck route choice preferences  
11 among long-haul, medium-haul, and short-haul distances.

12 To address the understudied issue, we categorize trips into three distinct scenarios based on  
13 travel distance: long-haul, medium-haul, and short-haul. We employ large-scale truck GPS data  
14 to empirically analyze truck route choice preferences across these freight demand. Compared to  
15 traditional Revealed Preference (RP) and Stated Preference (SP) survey data, GPS data offers  
16 more specific information about truck travel routes, making a more accurate identification of the  
17 disparities in truck route choice preferences. Subsequently, we propose a framework for the  
18 trucks route decision-making mechanisms. Based on this framework, we investigate the  
19 influences of different route attributes on truck route choice preferences and conduct a  
20 comprehensive analysis of the route choice mechanisms. Then, given the similarity among  
21 available routes, we employ the Path Size Logit (PSL) Model to quantify the effects, and  
22 compare the results obtained from the Multinomial Logit (MNL) Model. Finally, based on the

1 findings, we put forward suggestions for designing rules for urban truck route network under  
2 long-haul, medium-haul, and short-haul.

3 The potential theoretical and practical contribution of this study is two-fold. From a  
4 theoretical perspective, this study introduces a framework for understanding the mechanism  
5 behind truck route decision-making. This framework enables us to construct a comprehensive set  
6 of factors that influence preferred routes and facilitates a systematic analysis of the route choice  
7 mechanism. From a practical perspective, we discern differences and similarities in truck route  
8 preferences across long-haul, medium-haul, and short-haul. Our findings can provide insights for  
9 constructing the tailored truck route network, so as to effectively manage the truck traffic flow  
10 and reduce their impacts on the urban transportation systems.

11 The paper is organized as follows: Section 2 provides the literature review for truck route  
12 choice behavior and route choice preferences in various distance scenarios. Section 3 outlines the  
13 methodology, including decision rules, Multinomial Logit Model and Path Size Logit Model.  
14 Section 4 details the data collection and process, and Section 5 presents the results. The policy  
15 implications of truck route network for long-haul, medium-haul, and short-haul are provided in  
16 Section 6, followed by the conclusions in the final section.

## 17 **2. Literature review**

### 18 *2.1 Trucks route choice behavior*

19 Numerous studies have been conducted to analyze the route choices made by truck drivers  
20 or freight forwarders. Among them, the typical studies focus on the choice outcomes and  
21 influencing factors when it comes to toll roads (Toledo et al., 2013; Wang and Zhang, 2017;  
22 Wood, 2012; Zhou et al., 2009). Specifically, Tsirimpa et al. (2019) focused on examining the  
23 effect of toll payment on the route choice behavior of freight forwarders and truck drivers by

1 conducting a stated preferences (SP) survey experiment. The results showed that the value of  
2 time (VOT) varies between the alternatives (toll road and national road), and the value of VOT is  
3 higher on the toll road. Similarly, Sun et al. (2013) also conducted an SP experiment where  
4 drivers were asked to choose between two route alternatives with toll costs significantly differing.  
5 Rowell et al. (2014) investigated the truck routing priorities of freight companies through a  
6 survey involving shippers, carriers, and receivers concerning each item's influence on route  
7 choice. The results showed that minimizing travel costs and meeting customer requirements were  
8 priorities. Moreover, Feng et al. (2013) found that light truck drivers are significantly sensitive to  
9 road pricing, when exploring the influence of truck drivers' heterogeneity on route choice.

10 The above studies mainly used questionnaire data to explore the truck route choice behavior.  
11 Some scholars have shifted from using survey data to large-scale GPS records in recent years, to  
12 discuss the influencing factors or the preference characteristics of the truck route choice.  
13 Specifically, Toledo et al. (2020) use large streams of truck-GPS data to analyze intercity truck  
14 route choices incorporating toll road alternatives, and identify the influencing factors of route  
15 attributes, including travel times, tolls, distances, and road classifications. Luong et al. (2018)  
16 use the extensive database of 73,000 truck routes derived from 200 million GPS records to  
17 explore the trucks route choice diversity. The analysis suggests that short-haul truck travel  
18 exhibits greater diversity in route choice than long-haul travel, regarding the number of unique  
19 routes observed. Sharma et al. (2022) proposed a new two-step approach to fuse automated  
20 vehicle identification data and loop-detector data and use latent class choice analysis to capture  
21 the route choice preference in different segments of truck drivers based on these data sources.  
22 This type of data can offer advantages regarding positional precision and large sample size, and

1 help to identify route features. (Demissie and Kattan, 2022; Luong et al., 2018; Wang and  
2 Goodchild, 2014).

3 Furthermore, a few studies have provided valuable insights into route choice preferences in  
4 specific travel scenarios, with a particular emphasis on topics such as long-haul or intercity trips.  
5 Specifically, Knorrning et al. (2005) conducted an empirical analysis of long-haul truck drivers'  
6 route choice decision-making as they navigate the U.S. highway network, and found that time is  
7 a significant factor in the decision-making process. Toledo et al. (2020) also focused their  
8 analysis on intercity truck route choices incorporating toll road alternatives, and found that vast  
9 heterogeneous choices among drivers with different employment types and availability of  
10 electronic toll collection tags. Maoh et al. (2021) constructed six border delay scenarios to  
11 explore trucks' movements between Ontario, Canada, and the United States, and found that long-  
12 haul trips tend to favor the Ambassador Bridge crossing, which connects Windsor, Ontario, to  
13 Detroit, Michigan. In addition, Wang and Goodchild (2014) found that travel time, travel time  
14 reliability, and toll rates significantly influenced route choices during both peak and off-peak  
15 periods when they used truck GPS data to observe empirical responses to tolling.

16 While numerous studies have utilized diverse datasets to examine truck route choices, with  
17 some specifically delving into route preferences in distinct travel scenarios, limited research has  
18 been conducted to compare truck route preferences across varying distances. The disparities in  
19 the value of goods, considerations for timeliness, and cost control at different distances may lead  
20 to unique requirements for route attributes, shaping specific route preferences (Feng et al., 2013;  
21 Kinjarapu et al., 2022; Luong et al., 2018).

## 1 2.2 Route choice preference in various distance scenarios

2 Existing studies have suggested that route choice preferences vary across different travel  
3 distances. Specifically, Jou and Yeh (2013) employed a mixed logit model to investigate the  
4 freeway passenger car drivers' choice behavior concerning travel time and route choice across  
5 three distinct travel distances: short-distance, medium-distance, and long-distance. Their findings  
6 revealed a higher proportion of local road travelers opting for off-peak freeway routes,  
7 particularly when there was a greater percentage of toll reduction. This pattern also mirrored the  
8 preferences observed in short-distance trips; however, for medium-distance trips, the opposite  
9 trend was observed. In addition, they observed that the proportion of drivers choosing local roads  
10 for long-distance trips is relatively low, resembling the trend seen in medium-distance trips.  
11 Deng et al. (2020) analyzed the heterogeneous trip distance-based route choice behavior using  
12 the taxi trajectory data. The analysis of the marginal rate of substitution across short, medium,  
13 and long distances models indicated that a one-unit increase in left turns required a reduction in  
14 travel time by 1.02, 0.98, and 1.05 minutes for short, medium, and long distances, respectively.  
15 Yamamoto et al. (2018) discussed the heterogeneity of trip distance in the pedestrian route  
16 choice behavior, and found that the same level of detouring has a larger impact on route choice  
17 for shorter trips than on longer trips.

18 While several studies have delved into route choice preferences across long-haul, medium-  
19 haul, and short-haul travel scenarios, the predominant focus has been on passenger transport. In  
20 contrast to passenger transport, the realm of goods delivery introduces distinctive factors that  
21 influence truck route choice behavior. Drivers, in this context, typically factor in considerations  
22 such as the weight and/or size of the truck, driving restriction, and the sequence of addresses  
23 when making route decisions. Furthermore, large and heavy vehicles impose additional criteria

1 on route choice, encompassing road accessibility, gradient, and convenience for goods loading  
2 and unloading (Feng et al., 2013; Quak and de Koster, 2006). Hence, the results about the route  
3 choice preferences of passenger transport are not fully suitable for truck travel. Understanding  
4 the specifics of differences or similarities in truck route preferences between various distances  
5 and uncovering the underlying reasons for such variations need to be further explored.

### 6 **3. Methodology**

#### 7 *3.1 Decision rules*

8 The truck travel routes typically rely on individual decisions made by truck drivers or  
9 freight forwarders, and their decision-making result is influenced by the delivery demand and  
10 route characteristics (Jiang and Zhang, 2019; Tsirimpa et al., 2019). Specifically, truck travel is  
11 typically driven by the delivery demand. Before departure, route decision-makers obtain the  
12 delivery information including the value of the goods, the designated time window for delivery,  
13 and the imperative for cost control (Rowell et al., 2014). Subsequently, they need to make the  
14 route choice to ensure the complete and punctual delivery of goods at a minimal cost. In this  
15 process, the route decision-makers systematically evaluate the economic, safety, reliability, and  
16 driving convenience of the available routes, based on the characteristics of road geometry, tolls,  
17 and driving distance. Finally, they opt for the travel route that maximizes individual utility.

18 Diverse delivery demands entail distinct criteria encompassing economic, safety, reliability,  
19 and driving convenience when choosing the routes (Han et al., 2021; Jiang and Zhang, 2019;  
20 Kordonis et al., 2019; Papadopoulos et al., 2021; Xu et al., 2017). This diversity gives rise to  
21 varying preferences for routes based on specific demands. In addition, significant differences  
22 exist in delivery demands among long-haul, medium-haul, and short-haul. To be specific, long-  
23 haul freight often entails crossing urban agglomeration boundaries or covering considerable

1 distances between cities. Long-haul delivery goods typically comprise higher-value items, such  
2 as commodities, manufactured goods, and raw materials. Furthermore, they have lower  
3 requirements for timeliness, and travel costs tend to be higher and difficult to control (Cantillo et  
4 al., 2021; Hu et al., 2018; Zhu et al., 2023). For medium-haul trips, the goods typically consist of  
5 consumer goods, retail products, and items of moderate value, with flexible delivery timeliness  
6 and moderate costs and benefits (Akter and Hernandez, 2023; Pani et al., 2023; Zhu et al., 2023).  
7 However, in terms of short-haul trips, goods may mainly involve food, daily necessities, express  
8 parcels, etc. In this type of freight scenario, quick delivery is typically necessary, often strict  
9 requirements for timeliness while striving for lower costs (Akter and Hernandez, 2023; Giuliano  
10 et al., 2020; Zhu et al., 2023).

11 Based on the above content, we propose a framework for truck route decision mechanisms,  
12 as shown in Fig. 1. Based on this theoretical framework, we examine the differences in truck  
13 route preferences across three freight scenarios: long-haul, medium-haul, and short-haul.

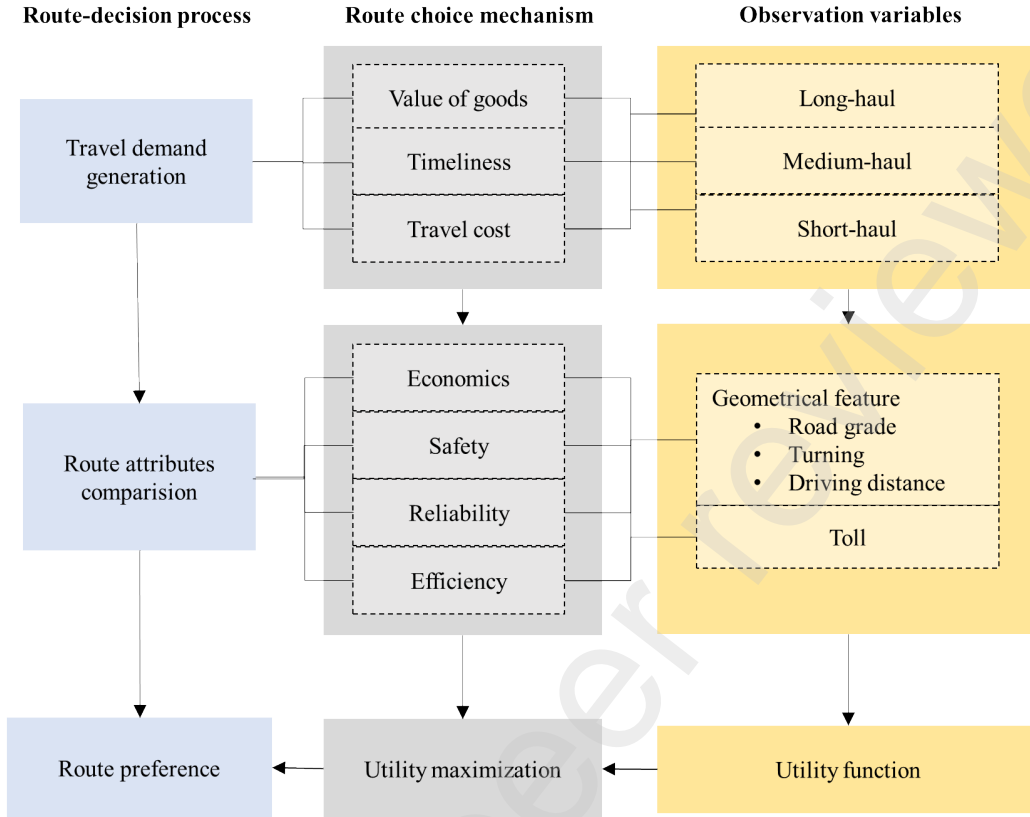


Fig. 1. Framework of route decision mechanism

### 3.2 Multinomial Logit Model

The Multinomial Logit (MNL) Model is commonly used to describe individual travel choice behavior. The model is based on the random utility theory, which assumes that drivers will choose the option with the greatest utility among their perceived alternatives. If we assume that the error terms of the utility function are independent and identically Gumbel distributed, the choice probability of each alternative  $i$  can be expressed as Equation 1. The model assumes a linear relationship between utility and each influencing factor. Hence, we have  $V_{in} = \sum_{k=1}^{K_i} \beta_{ik} X_{ink}$ .  $K$  is the influencing factor.

$$P_{in} = e^{V_{in}} / \sum_{i=1}^N e^{V_{in}} \quad (1)$$

where  $P_{in}$  is the probability of driver  $n$  choosing alternative  $i$ ;  $V_{in}$  is the utility of driver  $n$  choosing alternative  $i$ ;  $N$  is the number of choice set.

### 1 3.3 Path Size Logit Model

2 Typically, the alternative routes are often overlapping. Hence, this model introduces a path  
3 size correction term to address the issue of path overlap. This correction term partially mitigates  
4 the Independence of Irrelevant Alternatives (IIA) problem arising from the traditional Logit  
5 model's assumption of independently and identically distributed (IID) error terms. The path size  
6 correction factor quantifies the similarity of a route alternative with other route options present in  
7 the choice set and its values range from 0 to 1. A distinct route, which is unique and does not  
8 overlap with other route alternatives in the choice set, has a path size of 1. The path size  
9 correction for a route alternative  $i$  corresponding to a truck driver  $n$  is defined in Equation 2 as:

$$10 \quad PS_{in} = \sum_{a \in \Gamma_{in}} \left( \frac{l_a}{l_i} \right) \frac{1}{\sum_{j \in C_n} \delta_{aj}} \quad (2)$$

11 where  $a$  is a link in the route alternative  $i$ ;  $\Gamma_{in}$  is the set of links present in the route alternative  $i$ ;  
12  $l_a$  is the length of link  $a$ ;  $l_i$  is the length of route alternative  $i$ ;  $\sum_{j \in C_n} \delta_{aj}$  indicates the total  
13 number of route alternatives in choice set  $C_n$ , present in the choice set of a driver  $n$ , sharing link  
14  $a$ .

15 By including a path size (PS) correction factor, we deal with the correlation among route  
16 alternatives. Thus, the choice probability of a driver  $n$  to choosing a route alternative  $i$  is given  
17 by Equation 3.  $\beta_{ps}$  is the coefficient of the path-size term.

$$18 \quad P_{in} = e^{(V_{in} + \beta_{ps} PS_{in})} / \sum_{i=1}^N e^{(V_{in} + \beta_{ps} PS_{in})} \quad (3)$$

## 4. Data collection and process

We utilize GPS data obtained from heavy trucks in China, each with a weight exceeding 12 tons, to investigate their route choice preferences. The dataset comprises records from 2337 vehicles\*days, collected at 30-second intervals. Each record in the dataset encompasses key information, including the vehicle number, system timestamp, vehicle operation details, and vehicle location information. In this section, we elucidate the methodological steps involved in organizing the GPS data into trips and matching them with maps, generating the alternative choices set, and recognizing three travel scenarios.

### 4.1 Trips process

The original trajectory data requires further processing before it can be effectively modeled for route choice, including identification of trips and map matching. For the analysis, trips are characterized as travel originating from loading points to subsequent drop-off points, serving as destination stops. In practice, heavy trucks may pause at specific locations for various reasons, including loading and unloading activities, taking temporary rests, or encountering traffic congestion. We introduce two distinct categories of stops: freight-related stops and non-freight-related stops. Freight-related stops pertain to halts induced by freight-related activities like loading or unloading goods, necessitating specific identification. Conversely, non-freight-related stops encompass activities unrelated to freight behaviors, such as waiting at intersections, and encountering traffic congestion, which are not recognized as valid stops. Drawing on findings from freight surveys, the loading and unloading time for trucks often exceeds 10 minutes, and it's also similar to previous literature (Gong et al., 2015; Sarti et al., 2017; Yang et al., 2014). Hence, we establish a 10-minute threshold. Records exhibiting dwell times surpassing this

1 duration are identified as destination points, contributing to the precision of trajectory  
2 segmentation in capturing substantive freight-related stops while excluding non-relevant pauses.

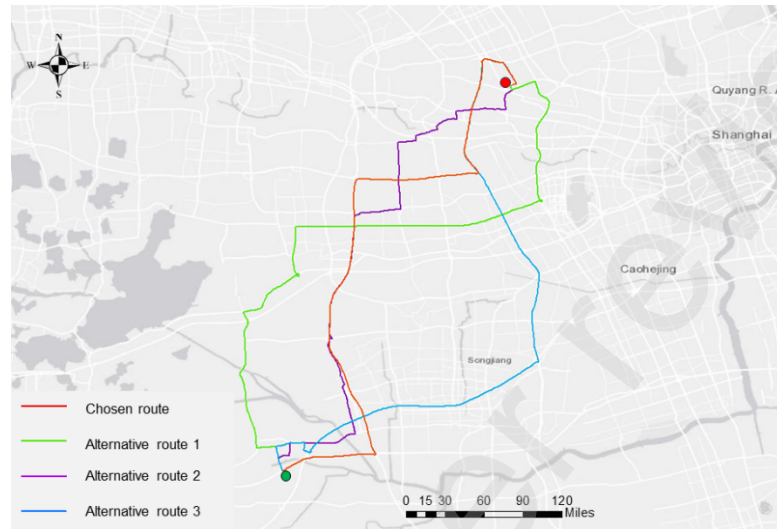
3 In terms of map matching, we adopt the geometric matching method, which involves  
4 querying road segments based on a buffer zone. Within this buffer zone, all road segments within  
5 a specific range (set at 50 meters in this study) are considered as candidate road segments for the  
6 current observation. Conversely, road segments beyond this range are excluded from  
7 consideration and assigned a probability of 0. The probability of a truck traveling on a specific  
8 candidate road segment is higher when the distance between the candidate road segment and the  
9 observation is smaller. In addition, the road network data used for map matching were extracted  
10 from the OpenStreetMap (OSM) GIS database.

#### 11 *4.2 Alternative choice set generation*

12 Analyzing route decision-making requires knowledge not only of the chosen option but also  
13 of the other available alternatives that were considered during the decision-making process.  
14 Therefore, a complete set of potential choices, known as the choice set, is essential for gaining  
15 insights into decision-making behavior. We utilized the AMap (AutoNavi Map) API to  
16 systematically create the set of alternative choices for each origin-destination (OD) pair. As a  
17 crucial navigation tool for drivers, this platform offers over ten route strategies, making it a  
18 preferred option among truck drivers when searching for travel routes.

19 Considering route searching costs and the possibility of route duplication, we employ the  
20 platform to investigate routes commonly recommended by the navigation system. These routes  
21 encompass options such as the shortest distance route, fastest route, lowest cost route, less  
22 highway route, and highway priority route. Subsequently, we conduct a thorough examination to  
23 identify and eliminate duplicates within the alternative choices set. This systematic approach

1 ensures a comprehensive analysis of various route characteristics while addressing the potential  
2 issue of redundancy in the dataset. The sample of the chosen route and alternative route are  
3 shown in Fig.2.



4  
5 Fig. 2. Sample of chosen route and alternative routes

#### 6 *4.3 Recognition of travel scenarios*

7 We categorize trips into long-haul, medium-haul, and short-haul using an index of travel  
8 distance, a method commonly employed in the literature (Deng et al., 2020; Jou and Yeh, 2013;  
9 Łukawska et al., 2023). To determine the thresholds for these categories, we initially distribute  
10 the samples evenly based on the distribution of trip lengths, as illustrated in Fig. 3. This method  
11 has been used in Łukawska et al. (2023). Among them, approximately 40% of the trips cover  
12 distances less than 50 km, while 30% fall within the 50 km to 150 km range, and about 30%  
13 extend beyond 150 km. Utilizing these delineations, trips covering less than 50 km are  
14 categorized as short-haul, those spanning 50 km to 150 km are classified as medium-haul, and  
15 trips exceeding 150 km are designated as long-haul. Secondly, in conjunction with the Origin-  
16 Destination (OD) distribution for each type of trip (Fig. 4), it becomes evident that short-haul  
17 trips predominantly pertain to intra-city travel, medium-haul trips encompass journeys between a

1 city and its adjacent regions, and long-haul trips entail extensive distances between cities and  
2 provinces. Therefore, the classification of the three scenarios, as outlined above, is deemed  
3 reasonable.

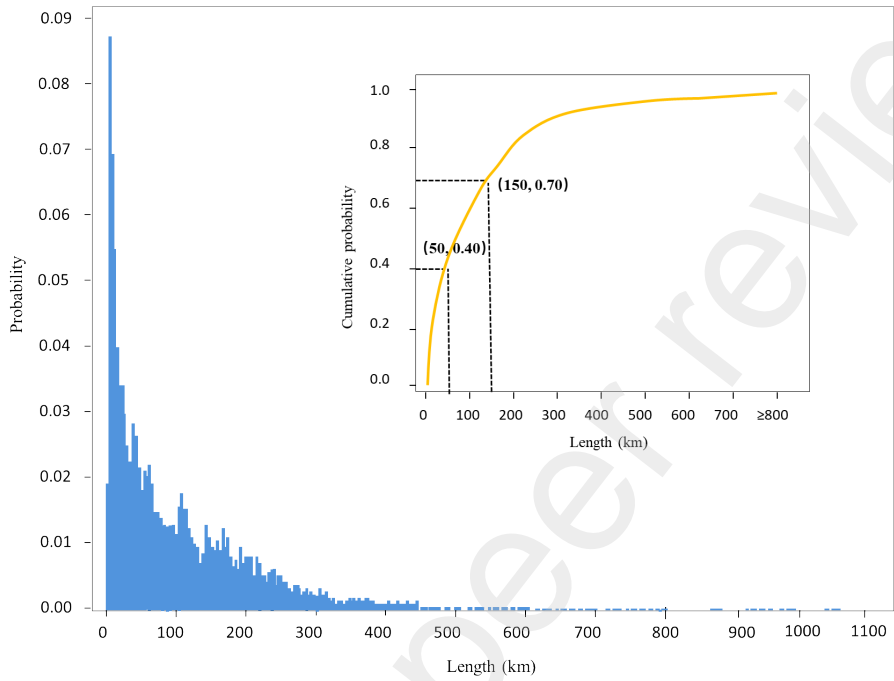
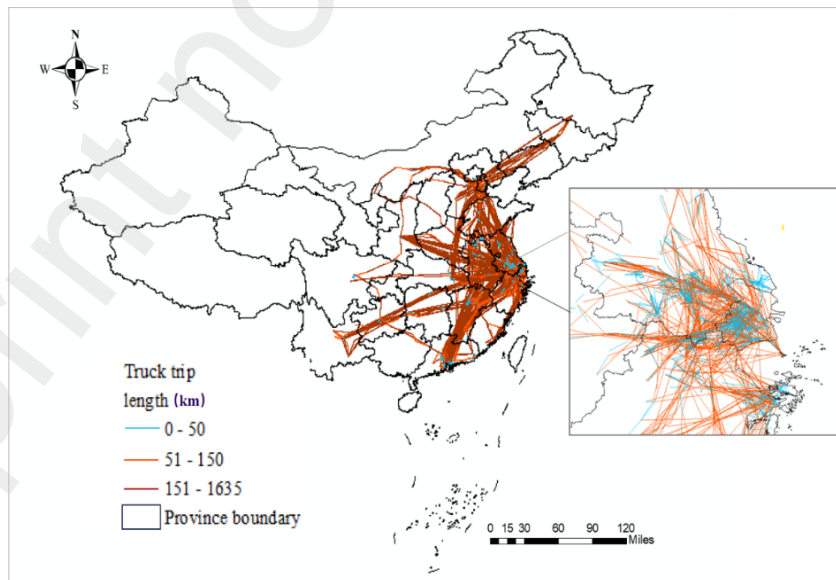


Fig. 3. Distribution of the length of trips



7

8

Fig. 4. Spatial distribution of all trips

# 1 **5. Results**

## 2 *5.1 Statistical analysis*

3 The dataset employed for model estimation consists of a total of 6966 trips, including 1982  
4 for long-haul travel, 2047 for medium-haul travel, and 2937 for short-haul travel. In addition, a  
5 total of 17376 alternative routes have been generated for these trips, with about 3 alternative  
6 routes per trip on average. In addition, we initially selected nine attributes of routes that we  
7 hypothesized to affect truck route choice preference. The descriptive statistics of attributes for  
8 chosen routes and alternative routes are as shown in Table 1. It reveals that for the variable of  
9 tolls, the statistical indicators of chosen routes surpass those of alternatives. Conversely,  
10 regarding the variable of turns, the opposite outcomes are observed. Regarding the motorway  
11 and sub-arterial road, the mean values of chosen routes exceed those of the alternatives. However,  
12 the results of arterial road and branch road are opposite.

13 Moreover, we conduct a comparative analysis of the characteristics of the chosen routes  
14 across long-haul, medium-haul, and long-haul trips, as presented in Table 2. The findings reveal  
15 considerable variation in tolls and fractions on specific roads among these three scenarios.  
16 Specifically, long-haul trips exhibit generally elevated statistical indicators for tolls and  
17 motorway, in comparison to short-haul and medium-haul trips. Conversely, short-haul trips  
18 demonstrate the highest values in terms of turns, arterial road, sub-arterial road, branch road, and  
19 path size.

20

Table 1 Description of variables and descriptive statistics of the chosen routes and alternatives

Variables	Description	Chosen route			Alternatives		
		Max	Mean	Min	Max	Mean	Min
Motorway	Fraction of route distance that used motorway/freeway (%)	0.99	0.44	0.00	0.99	0.28	0.00
Arterial Road	Fraction of route distance that used trunk and primary roads (%)	1.00	0.36	0.00	1.00	0.53	0.00
Sub-Arterial Road	Fraction of route distance that used secondary and tertiary roads (%)	1.00	0.16	0.00	1.00	0.11	0.00
Branch Road	Fraction of route distance that used unclassified and residential roads (%)	1.00	0.03	0.00	1.00	0.09	0.00
Turns	Number of turns per kilometer (turns/km)	2.45	0.18	0.00	2.78	0.23	0.00
Travel distance	Length of route (km)	1959.22	133.27	1.02	2033.75	179.02	1.10
Tolls	Toll cost amount (RMB)	2137.00	95.02	0.00	929.00	55.23	0.00
Path Size	The overlap indicator for alternative paths for the same trip	0.82	0.46	0.08	0.88	0.51	0.25

1

Table 2 Descriptive statistics of the chosen routes across three scenarios

Variables	Scenarios	Max	Mean	Min	S.D.
Motorway	Long-haul	0.99	0.82	0.00	0.32
	Medium- haul	0.99	0.47	0.00	0.41
	Short-haul	0.82	0.16	0.00	0.31
Arterial Road	Long-haul	1.00	0.15	0.00	0.28
	Medium- haul	1.00	0.42	0.00	0.37
	Short-haul	1.00	0.64	0.00	0.33
Sub-Arterial Road	Long-haul	0.70	0.03	0.00	0.05
	Medium- haul	0.86	0.09	0.00	0.13
	Short-haul	0.93	0.11	0.00	0.28
Branch Road	Long-haul	0.16	0.00	0.00	0.01
	Medium- haul	0.34	0.01	0.00	0.03
	Short-haul	1.00	0.05	0.00	0.12
Turns	Long-haul	0.20	0.04	0.00	0.03
	Medium- haul	0.56	0.10	0.01	0.06
	Short-haul	2.24	0.33	0.02	0.24
Travel distance	Long-haul	1959.22	342.57	150.03	278.35
	Medium- haul	149.94	93.56	50.04	28.68
	Short-haul	50.00	21.54	2.55	13.58
Tolls	Long-haul	2137.00	281.24	0.00	348.71
	Medium- haul	430.00	44.53	0.00	62.26
	Short-haul	194.00	5.93	0.00	20.63
Path Size	Long-haul	0.79	0.35	0.09	0.27
	Medium- haul	0.80	0.47	0.08	0.28
	Short-haul	0.82	0.52	0.08	0.31

2

3 *5.2 Model results*4 *5.2.1 Model comparison*

5 Table 3 presents the parameter estimated results of MNL models and PSL models of long-  
6 haul, medium-haul, and short-haul trips. It shows that the significance and the symbolism of the  
7 influencing factors for PSL model and MNL model are almost the same in each scenario.

1 However, the adjusted R-squared of PSL model surpasses those of MNL model in each scenario,  
2 indicating that the PSL model with the route overlapping parameter, can more accurately capture  
3 the genuine patterns of the truck route choice preference. Hence, our subsequent analysis of truck  
4 route choice preferences will be grounded on the insights derived from the PSL model.

### 5 *5.2.2 Route choice preference*

6 Based on the parameter estimated results of PSL models in Table 3, we identify the  
7 characteristics of preferent roads among long-haul, medium-haul, and short-haul trips. For long-  
8 haul trips, the variables related to motorways and sub-arterial roads exhibit significantly positive  
9 effects on route preferences. Conversely, the variable associated with arterial roads shows no  
10 significant impact, while the branch road variable demonstrates significantly negative effects.  
11 Similar patterns are observed for medium-haul trips, indicating a preference for routes  
12 comprising a combination of motorways and sub-arterial roads for long-haul and medium-haul  
13 trips. For short-haul trips, while all types of roads exhibit significantly negative impacts on route  
14 preferences, the negative effect of sub-arterial roads stands out as the least among them,  
15 indicating a preference for sub-arterial roads over other types in short-haul trips.

16 Based on the above results, we find that branch roads are not prioritized across the three trip  
17 categories, while sub-arterial roads are the preferred choice. This implies that sub-arterial roads  
18 function as terminal ways to deliver goods to their ultimate destinations, thereby drawing a  
19 significant usage of trucks. Secondly, arterial roads are not considered choices for long-haul and  
20 medium-haul trips, while motorways are favored for these two scenarios. The reason may be that  
21 their relatively lower speed and safety standards compared to motorways, as well as reduced  
22 accessibility compared to sub-arterial roads. In contrast, motorways primarily accommodate

1 long-haul and medium-haul trips. This preference may be because motorways offer advantages  
2 such as higher speed, enhanced safety, and greater stability, making them the preferred choice  
3 for relatively long distances.

4 In addition, the variable of turns exhibits a significantly negative impact on medium-haul  
5 and short-haul trips, meaning that the routes with fewer turns are favored for these two trips. This  
6 phenomenon may be because the high fraction of urban local roads for medium-haul and short-  
7 haul trips. Given the complexities involved in navigating heavy-duty trucks, the route-maker  
8 decision often favors the route with fewer turns to ensure the safety of both the vehicle and its  
9 cargo. However, this effect is not significant for the long-haul trip.

10 Furthermore, there are some shared characteristics observed in the parameters of travel  
11 distance and tolls among these three trips. Specifically, travel distance has a significantly  
12 negative effect on route choice preference, as expected. However, the toll variable exhibits  
13 significantly positive effects on all three types of trips. This phenomenon may be attributed to the  
14 preference for motorways observed in both long-haul and medium-haul trips, along with the  
15 secondary preference for motorways evident in short-haul trips. This indicates that despite the  
16 additional cost, route decision-makers may opt for toll roads due to their potential advantages,  
17 such as faster travel times, better road conditions, or safer driving. In addition, the truck travel  
18 dataset in this paper primarily focuses on the Yangtze River Delta region, where goods of high  
19 value are predominant. Consequently, there may be less attention paid to toll costs.

20 Variable related to path size aims to account for the impact of route overlap, with larger  
21 values indicating reduced overlap among routes. The coefficient for the logarithm of Path Size  
22 ( $\ln(\text{Path Size})$ ) exhibits different effects across the three scenarios. Specifically, it has a  
23 significant negative effect on long-haul and medium-haul trips, suggesting that route decision-

1 makers tend to prefer routes that have higher congruence with other routes. This phenomenon  
 2 may be attributed to the relatively limited inter-city road network, leading attractive routes to  
 3 often coincide with other options in the choice set. Moreover, these highly congruent routes may  
 4 provide the additional advantage of flexibility, allowing for route adjustments to address sudden  
 5 traffic issues. However, for short-haul, the parameter of path size shows a positive effect on  
 6 preference route, which means short-haul trips tend to favor routes with lower congruence. This  
 7 may be because that short-haul trips frequently take place within urban environments  
 8 characterized by a higher density of intersections. Compared to the roads with high congruence,  
 9 lower congruence roads typically entail fewer intersections and more direct, thereby offering  
 10 truck drivers a more ease and safer driving experience, while also helping them circumvent  
 11 typical traffic congestion.

12

Table 3 Parameter estimation results for three scenarios

parameters	PSL model			MNL model		
	value	std err	p-value	value	std err	p-value
<b>Long-haul</b>						
Constant	-3.970	1.725	0.021	-2.801	1.699	0.099
Motorway	3.636	1.727	0.035	3.726	1.704	0.029
Arterial Road	1.727	1.735	0.319	1.207	1.711	0.481
Sub-Arterial Road	4.769	1.784	0.008	4.130	1.762	0.019
Branch Road	-47.64	3.875	0.000	-54.074	3.985	0.000
Turns	0.067	0.473	0.887	0.002	1.631	0.033
Travel distance	-0.005	0.000	0.000	-0.006	0.000	0.000
Tolls	0.009	0.001	0.000	0.009	0.001	0.000
Ln(Path Size)	-0.887	0.073	0.000			
Observations		7672			7672	
Adjusted rho square		0.457			0.440	
Log-likelihood		-2379.9			-2455.9	

<b>Medium-haul</b>						
Constant	-1.210	0.750	0.107	-0.541	0.759	0.476
Motorway	1.688	0.747	0.024	1.888	0.759	0.013
Arterial Road	0.766	0.745	0.304	0.810	0.757	0.285
Sub-Arterial Road	2.116	0.762	0.005	2.151	0.775	0.006
Branch Road	-11.921	1.248	0.000	-11.775	1.255	0.000
Turns	-4.384	0.498	0.000	-5.503	0.503	0.000
Travel distance	-0.008	0.001	0.000	-0.010	0.001	0.000
Tolls	0.004	0.001	0.000	0.005	0.001	0.000
Ln(Path Size)	-0.600	0.227	0.000			
Observations		7709				7709
Adjusted rho square		0.164				0.152
Final log-likelihood		-3731.0				-1894.2
<b>Short-haul</b>						
Constant	6.474	0.379	0.000	5.885	0.381	0.000
Motorway	-2.427	0.375	0.000	-3.007	0.381	0.000
Arterial Road	-3.306	0.361	0.000	-3.823	0.369	0.000
Sub-Arterial Road	-1.582	0.366	0.000	-1.946	0.374	0.000
Branch Road	-7.373	0.407	0.000	-7.534	0.412	0.000
Turns	-4.011	0.145	0.000	-3.651	0.137	0.000
Travel distance	-0.080	0.003	0.000	-0.068	0.003	0.000
Tolls	0.026	0.002	0.000	0.021	0.002	0.000
Ln(Path Size)	0.684	0.051	0.000			
Observations		9621				9621
Adjusted rho square		0.273				0.256
Final log-likelihood		-2631.8				-2669.4

1

### 2 5.2.3 Marginal effects

3 To assess the comparative sensitivity of variables across the three scenarios, we calculate

4 the marginal effects of variables with significant effects in each scenario, as delineated in Table 4.

1 First, it shows that the presence of branch roads has the largest influence on the route choice in  
2 each scenario. Specifically, 1 unit (1%) increase in the proportion of branch roads, the  
3 probability of choosing this route decreases by 4.691% in long-haul trips, 1.920% in medium-  
4 haul trips, and 1.143% in short-haul trips, respectively. Additionally, the marginal effect of  
5 branch roads is pronounced in long-haul trips, followed by medium-haul and the least in short-  
6 haul trips, suggesting that trucks' avoidance of branch roads increases with longer trip distances.

7 Second, the marginal effect of the turns ranks second for both medium-haul and short-haul  
8 trips. This indicates that convenience of operation and safety significantly affect route preference  
9 for both distance scenarios. Specifically, when the number of turns increases by 1 per kilometer,  
10 the probabilities of choosing this route decrease by 0.706% and 0.622% for medium-haul and  
11 short-haul trips, respectively.

12 Third, the route choices of long-haul and medium-haul trips are also sensitive to the  
13 variables of motorway and sub-arterial road. However, we find that long-haul trips exhibit  
14 greater sensitivity to motorway and sub-arterial roads compared to medium-haul trips.  
15 Specifically, a 1% increase in the proportion of motorways leads to a 0.358% increase in the  
16 probability of selecting this route for long-haul trips, whereas it results in a 0.272% increase for  
17 medium-haul trips. Similarly, a 1% increase in the proportion of sub-arterial roads results in a  
18 0.470% increase in the likelihood of choosing this route for long-haul trips, but only a 0.341%  
19 increase for medium-haul trips. These findings suggest that longer-distance travel may prioritize  
20 faster routes provided by motorways. Simultaneously, it uses the sub-arterial roads to complete  
21 the terminal transportation.

22 Furthermore, the marginal effect of travel distance and tolls are relatively small, but they  
23 also exhibit variability across these three scenarios. Specifically, when the travel distance

1 increases 1 unit (1 kilometer), the probability of choosing this route decreases by 0.001% in both  
 2 long-haul and medium-haul trips, and 0.012% in short-haul trips, respectively. However, this  
 3 marginal effect in short-haul trips is more pronounced compared to this in long-haul and  
 4 medium-haul trips, meaning that short-haul trips demonstrate the highest sensitivity to changes  
 5 in travel distance when compared to long-haul and medium-haul trips, and more tend to the  
 6 shortest distance route. In addition, the marginal effect of tolls on long-haul and medium-haul  
 7 trips are less pronounced compared to this in short-haul trips, suggesting that long-distance travel  
 8 is comparatively insensitive to tolls change.

Table 4 Marginal effects of significant variables across three scenarios

Variables	Long-haul	Medium-haul	Short-haul
Motorway	0.358	0.272	-0.376
Arterial Road	/	/	-0.513
Sub-Arterial Road	0.470	0.341	-0.245
Branch Road	-4.691	-1.920	-1.143
Turns	/	-0.706	-0.622
Travel distance	-0.001	-0.001	-0.012
Tolls	0.001	0.001	0.004
Path Size	-0.086	-0.096	0.106

9

### 10 5.3 Route choice mechanism

11 We find that while the combination of motorways and sub-arterial roads is preferred for  
 12 both long-haul and medium-haul trips, long-haul trips exhibit a higher sensitivity to motorways  
 13 and sub-arterial roads compared to medium-haul trips. These findings suggest that longer-  
 14 distance travel may prioritize faster and more accessible routes provided by motorways and sub-  
 15 arterial roads. Given that long-distance travel typically entails greater uncertainty as the travel

1 distance increase (Cantillo et al., 2021; Hu et al., 2018; Zhu et al., 2023), route decision-makers  
2 may pay more attention to the efficiency and reliability of the route. Hence, decision-makers  
3 with long-distance travel usually select routes with high-grade roads, characterized by fewer  
4 interference, faster speeds, and enhanced safety. Moreover, long-haul and medium-haul trips also  
5 exhibit less sensitivity to changes in tolls. On the one hand, higher travel costs make it less  
6 sensitive to tolls (Toledo et al., 2020; Wang and Goodchild, 2014; Wood, 2012; Zhou et al.,  
7 2009). On the other hand, they tend to prefer some motorways offering faster speeds despite  
8 higher toll charges. This observation further confirms that longer-distance travel places greater  
9 emphasis on travel efficiency while somewhat reducing the attention on travel economics. In  
10 addition, given the value of goods in long-haul and medium-haul trips is higher than that in  
11 short-haul trips, the preferred route with high-grade road and higher tolls can be understood.

12 In the context of short-haul trips, the preferred route characteristics also underscore their  
13 emphasis on travel safety, efficiency, and reliability. Specifically, their preferences incline  
14 towards routes with fewer turns, more direct, and shorter travel distances. Short-haul trips  
15 commonly favor local low-grade roads, such as sub-arterial roads, which typically feature  
16 multiple intersections. Therefore, opting for such routes facilitates the avoidance of congestion,  
17 and promotes ease of driving and reliability, all while improving driving safety concurrently.  
18 Additionally, short-haul trips exhibit the highest sensitivity to changes in travel distance  
19 compared to long-haul and medium-haul trips. On one hand, the decrease in travel distance leads  
20 to an increase in sensitivity to travel distance, which is similar to the previous studies (Łukawska  
21 et al., 2023; Toledo et al., 2020). On the other hand, short-distance delivery demands frequently  
22 include essential items such as daily necessities, food, and fast-moving consumer goods, which  
23 often necessitate urgent and timely delivery (Giuliano et al., 2020; Zhu et al., 2023).

1 Consequently, any increase in travel distance can result in extended delivery times, presenting a  
2 heightened sensitivity to travel distance for delivering these goods (Hess et al., 2015; Knorrning et  
3 al., 2005; Quattrone and Vitetta, 2011).

## 4 **6. Policy implications**

5 Based on these findings, we propose a few strategies for designing an urban truck route  
6 network to accommodate diverse freight demand types with varying travel distances. Specifically,  
7 this network can be categorized into two main segments: (1) interregional trunk routes that  
8 primarily accommodate long-haul and medium-haul trucking and (2) local routes that mainly  
9 serve short-haul trucking. Specific trucks are recommended to follow truck routes to the greatest  
10 extent possible; going off the routes to avoid traffic could lead to traffic fines subject to certain  
11 regulated zones and time periods. The real-time navigation system on smartphones could  
12 incorporate the truck route network when providing navigation suggestions to truck drivers so  
13 that violations can be further reduced. Specific considerations on designing the truck route  
14 network are shown as follows.

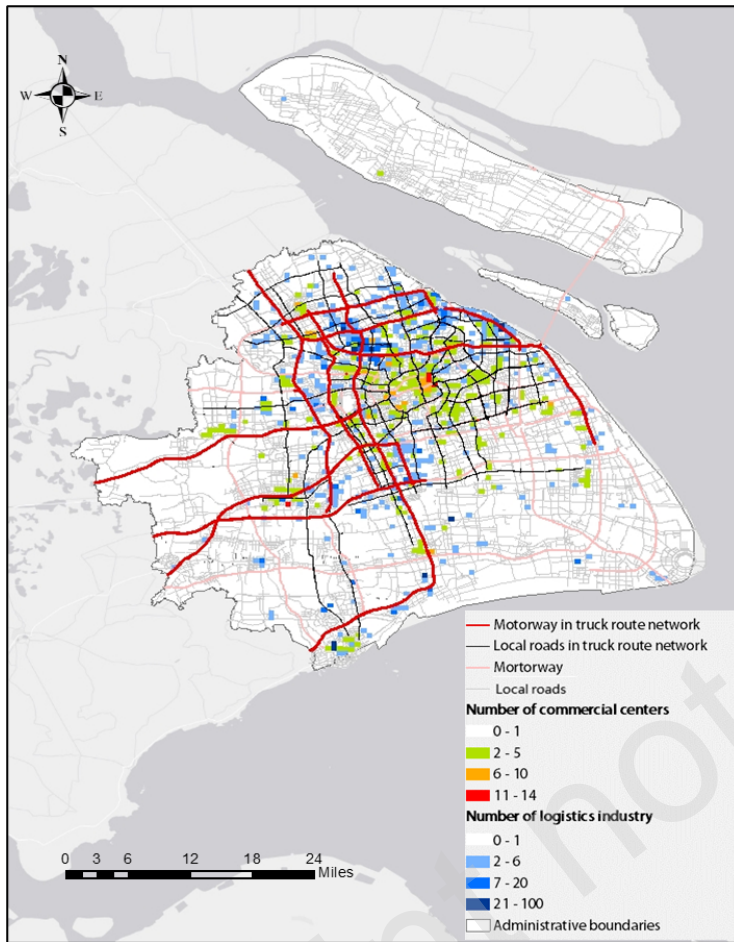
15 When designing the interregional trunk routes, planners may consider placing emphasis on  
16 prioritizing freeways linking regions with significant freight connections, so as to construct the  
17 main skeleton for the truck route network. The selected motorways should be able to provide the  
18 most time-saving route options. In this way, long-haul and medium-haul truck drivers could  
19 make the best use of the truck route network through interregional corridors, thus avoiding the  
20 serious congestion in the high-density urban areas.

21 With regard to the local routes, attention should be paid to arterials and secondary roads  
22 between zones with high concentrations of freight related establishments including fulfillment  
23 centers, warehouses, and retail stores. Planners may consider establishing a grid-like sub-

1 network with intervals twice or three times as the existing road network. Such sub-network  
2 would provide short-haul urban delivery trucks conveniences to travel within the central areas.  
3 After all, the central areas are filled with freight demand and delivery trucks deserve more access  
4 to accommodate such demand.

5 In order to better illustrate the design principles, we again utilize Shanghai city as the case  
6 study. Renowned as a global trade hub, Shanghai has witnessed the proliferation of freight  
7 establishments in recent years (Qin et al., 2023; Yang et al., 2022b). We focus on the areas with  
8 massive freight demand and try to formulate a truck route network serving both long-haul and  
9 short-haul truck movement. It is intuitive to designate the major inter-province motorway as the  
10 trunk freight corridors that provide capacities for large-volume interregional truck flows (see the  
11 Fig. 5). Long-haul and medium-haul trucks predominantly travel along these designated truck  
12 routes (as illustrated in Figure 6), according to the data set we presented above.

13 For the local truck routes, direct connections between the urban core and a multitude of  
14 warehousing facilities are established. These routes radiate from the urban core area,  
15 characterized by a high concentration of commercial centers, and typically utilize certain  
16 arterials and primary surface roads, as illustrated in Fig. 5. Along these truck routes, short-haul  
17 trucks can efficiently reach their destinations via the most direct and fewer turns. The selected  
18 short-haul trucking (as presented in Fig. 6) exactly relies on this network to complete the main  
19 trip.



1

2

Fig. 5. Truck route network in Shanghai City

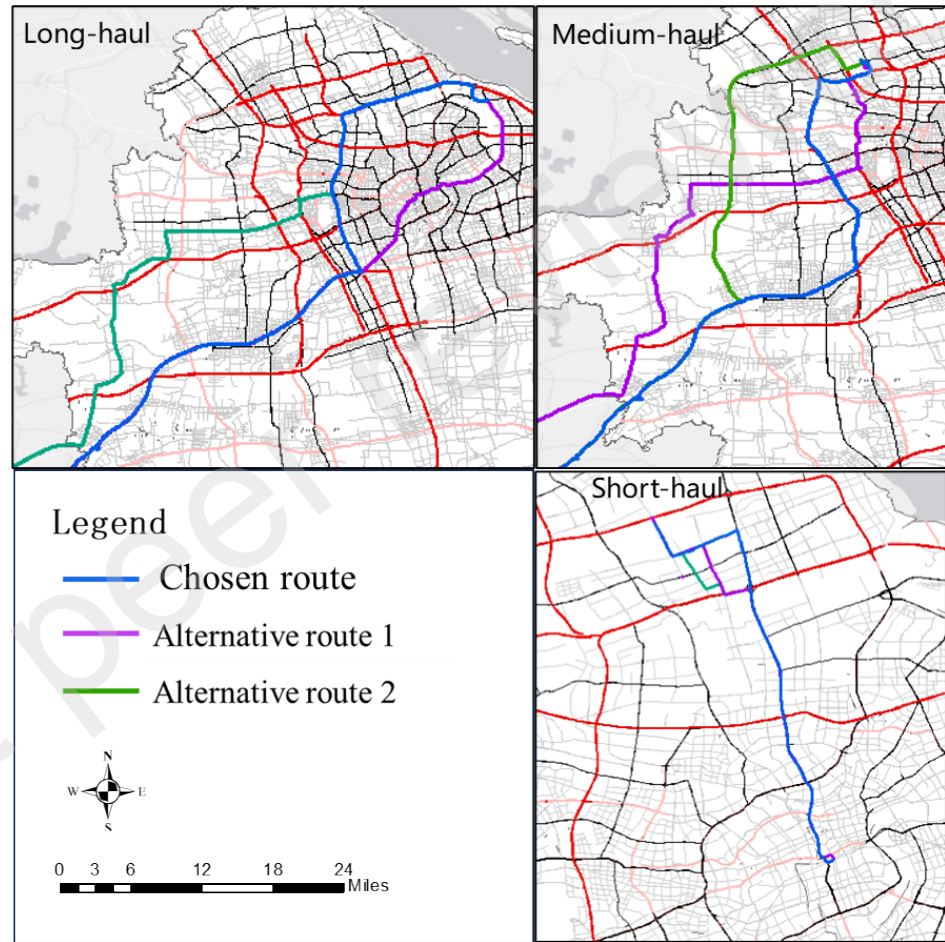
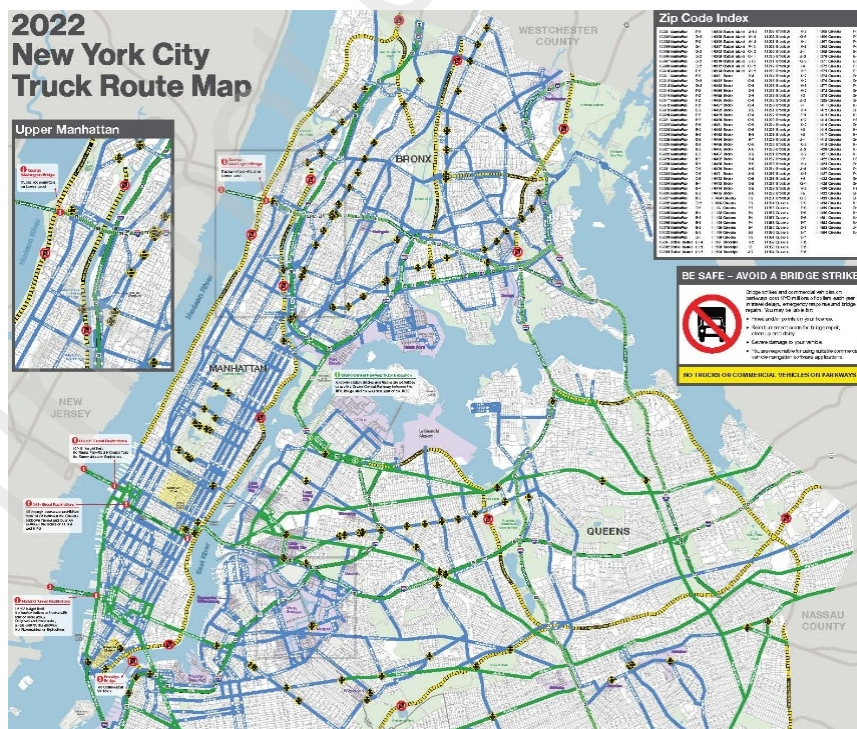


Fig.6. Samples for Long-haul, medium-haul, and short-haul

1 In addition, the proposed design principles for the truck route network resemble those found  
2 in the New York City's truck route map, as shown in Fig. 7. Specifically, the truck route  
3 networks in New York are divided into local truck routes and through truck routes. Among these,  
4 the local truck route network permits trucks with origins or destinations for delivery, loading, or  
5 servicing within the respective borough to utilize. Through truck route networks allow trucks  
6 without origins or destinations within the borough to use the routes (NYC, Department of  
7 Transportation, 2022). We observe that the local truck route network (blue lines) offers the  
8 shortest and least convoluted routes for trucks to navigate safely and efficiently. In addition, the  
9 report indicates that nearly one-third of all serious injury and fatality crashes involving trucks  
10 happened on non-truck routes (NYC, Department of Transportation, 2022). Therefore, these  
11 designated truck route networks play a pivotal role in enhancing urban traffic safety.  
12 Concurrently, our findings validate the rationale behind the design of these truck route networks.



13  
14

Fig. 7. New York City Truck Route Map

## 1 **7. Conclusions**

2 This paper aims to investigate the variations and commonalities in route choice preferences  
3 among trucks undertaking short-haul, medium-haul, and long-haul, and uncover the underlying  
4 mechanisms governing route choice behavior. Considering the overlapping of available routes,  
5 we use the Path Size Logit model to explore the route choice preference, and utilize truck GPS  
6 data to conduct empirical analysis within the framework of route decision mechanisms. The  
7 significant contributions of this research are threefold. Firstly, it provides a novel understanding  
8 the distinctions and commonalities in truck route preferences across long-haul, medium-haul,  
9 and short-haul, thereby shedding light on a previously overlooked research area. Second, it offers  
10 a systematic framework for analyzing truck route choice preferences, which is helpful to reveal  
11 the mechanism of truck route choice behavior. Third, the discoveries gleaned from this research  
12 can offer insights into designing a tailored truck route network for long-haul, medium-haul, and  
13 short-haul trips. This tailored approach is pivotal for efficiently managing truck traffic flows and  
14 alleviating their impact on the urban transportation system.

15 We find that while the characteristics of preferred routes vary across long-haul, medium-  
16 haul, and short-haul trips, they collectively reflect the consideration of travel efficiency, safety,  
17 and reliability in the decision-making process. Specifically, all these freight demands incline to  
18 the short distance routes, while short-haul trips exhibit the highest sensitivity to the travel  
19 distance. In addition, long-haul and medium-haul trips tend to favor routes that combine  
20 motorways and sub-arterial roads, while long-haul trips present higher sensitivity. However,  
21 short-haul trips prefer the route characterized by few turns, and a tendency towards sub-arterial  
22 roads as the last-mile delivery ways. Finally, we propose different truck route network design

1 principles appropriating for long-haul, medium-haul, and short-haul trips to better manage truck  
2 travel routes.

3       There are some shortcomings in this paper. First, we assume that decision-makers are  
4 rational and their choices are driven by utility maximization. However, it's important to  
5 acknowledge that route decision-makers may also be influenced by bounded rationality and  
6 individual psychological perceptions, such as attitudes and habits, which were not measured in  
7 this study. Future research could explore route preferences under the influence of habit to gain a  
8 more comprehensive understanding of route choice preference. Second, the lack of certain  
9 information about route decision-makers in the route choice model, which is inherent to the  
10 limitations of GPS data. In future studies, integrating survey data with large-scale GPS data  
11 could compensate for these deficiencies and provide a more comprehensive understanding of  
12 route preferences. Third, the truck travel dataset in this paper primarily focuses on the Yangtze  
13 River Delta region, where goods of high value are predominant. Consequently, route decision-  
14 makers tend to allocate less attention to economic factors. In future research, it would be  
15 beneficial to utilize more comprehensive datasets encompassing a broader range of goods to  
16 enhance the understanding of route choice mechanisms.

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## References

- Akter, T., Hernandez, S. (2023) Representative truck activity patterns from anonymous mobile sensor data. *International Journal of Transportation Science and Technology* 12, 492-504.
- Cantillo, L.-A., Cantillo, V., Miranda, P.A. (2021) Optimisation approach to solve the truck loading and delivery problem at long haul distances with heterogeneous products and fleet. *International Journal of Operational Research* 40, 92-116.
- Demissie, M.G., Kattan, L. (2022) Estimation of truck origin-destination flows using GPS data. *Transportation Research Part E: Logistics and Transportation Review* 159.
- Deng, Y., Li, M., Tang, Q., He, R., Hu, X. (2020) Heterogenous Trip Distance-Based Route Choice Behavior Analysis Using Real-World Large-Scale Taxi Trajectory Data. *Journal of Advanced Transportation* 2020, 1-16.
- Feng, T., Arentze, T., Timmermans, H. (2013) Capturing preference heterogeneity of truck drivers' route choice behavior with context effects using a latent class model. *European journal of transport and infrastructure research* 13.
- Giuliano, G., Dessouky, M., Dexter, S., Fang, J., Hu, S., Steimetz, S., O'Brien, T., Miller, M., Fulton, L. (2020) Developing Markets for Zero Emission Vehicles in Short Haul Goods Movement.
- Giuliano, G., Kang, S., Yuan, Q. (2016) Spatial dynamics of the logistics industry and implications for freight flows, No. NCST-20160600.
- Gong, L., Sato, H., Yamamoto, T., Miwa, T., Morikawa, T. (2015) Identification of activity stop locations in GPS trajectories by density-based clustering method combined with support vector machines. *Journal of Modern Transportation* 23, 202-213.
- Han, Q., Sun, Y., Wu, Q., Bai, Z. (2021) Research on optimization model of logistics transportation truck path considering environmental impact: Experimental data from Xiqing District, Tianjin. *Journal of Advanced Transportation* 2021, 1-12.
- Hess, S., Quddus, M., Rieser-Schüssler, N., Daly, A. (2015) Developing advanced route choice models for heavy goods vehicles using GPS data. *Transportation Research Part E: Logistics and Transportation Review* 77, 29-44.
- Holeczek, N. (2019) Hazardous materials truck transportation problems: A classification and state of the art literature review. *Transportation Research Part D: Transport and Environment* 69, 305-328.
- Hu, W., Toriello, A., Dessouky, M. (2018) Integrated inventory routing and freight consolidation for perishable goods. *European Journal of Operational Research* 271, 548-560.
- Jiang, Y., Zhang, J. (2019) Interaction between company Manager's and Driver's decisions on expressway routes for truck transport. *Transport Policy* 76, 1-12.
- Jou, R.-C., Yeh, Y.-C. (2013) Freeway passenger car drivers' travel choice behaviour in a distance-based toll system. *Transport Policy* 27, 11-19.
- Kinjarapu, A., Demissie, M.G., Kattan, L., Duckworth, R. (2022) Applications of Passive GPS Data to Characterize the Movement of Freight Trucks—A Case Study in the Calgary Region of Canada. *IEEE Transactions on Intelligent Transportation Systems* 23, 9210-9225.
- Knorrning, J.H., He, R., Kornhauser, A.L. (2005) Analysis of route choice decisions by long-haul truck drivers. *Transportation Research Record* 1923, 46-60.

Kordonis, I., Dessouky, M.M., Ioannou, P.A. (2019) Mechanisms for cooperative freight routing: Incentivizing individual participation. *IEEE Transactions on Intelligent Transportation Systems* 21, 2155-2166.

Lukawska, M., Paulsen, M., Rasmussen, T.K., Jensen, A.F., Nielsen, O.A. (2023) A joint bicycle route choice model for various cycling frequencies and trip distances based on a large crowdsourced GPS dataset. *Transportation Research Part A: Policy and Practice* 176.

Luong, T.D., Tahlyan, D., Pinjari, A.R. (2018) Comprehensive Exploratory Analysis of Truck Route Choice Diversity in Florida. *Transportation Research Record: Journal of the Transportation Research Board* 2672, 152-163.

Ma, X., Wang, Y., McCormack, E., Wang, Y. (2016) Understanding Freight Trip-Chaining Behavior Using a Spatial Data-Mining Approach with GPS Data. *Transportation Research Record: Journal of the Transportation Research Board* 2596, 44-54.

Maoh, H., Dimatulac, T., Khan, S., Litwin, M. (2021) Studying border crossing choice behavior of trucks moving between Ontario, Canada and the United States. *Journal of Transport Geography* 91.

Nadi, A., Sharma, S., van Lint, J.W.C., Tavasszy, L., Snelder, M. (2022) A data-driven traffic modeling for analyzing the impacts of a freight departure time shift policy. *Transportation Research Part A: Policy and Practice* 161, 130-150.

NYC (Department of Transportation, 2022) Truck Smart Guide-What You Need to Know Before You Go. Retrieved from <https://www.nyc.gov/html/dot/downloads/pdf/truck-smart-guide.pdf>.

Pani, A., Sahu, P.K., Tavasszy, L., Mishra, S. (2023) Freight activity-travel pattern generation (FAPG) as an enhancement of freight (trip) generation modelling: Methodology and case study. *Transport Policy* 144, 34-48.

Papadopoulos, A.-A., Kordonis, I., Dessouky, M.M., Ioannou, P.A. (2021) Personalized Pareto-improving pricing-and-routing schemes for near-optimum freight routing: An alternative approach to congestion pricing. *Transportation Research Part C: Emerging Technologies* 125, 103004.

Qin, Z., Liang, Y., Yang, C., Fu, Q., Chao, Y., Liu, Z., Yuan, Q. (2023) Externalities from restrictions: examining the short-run effects of urban core-focused driving restriction policies on air quality. *Transportation Research Part D: Transport and Environment* 119, 103723.

Quak, H., de Koster, R. (2006) The impacts of time access restrictions and vehicle weight restrictions on food retailers and the environment. *European Journal of Transport and Infrastructure Research (Print)*, 131-150.

Quattrone, A., Vitetta, A. (2011) Random and fuzzy utility models for road route choice. *Transportation Research Part E: Logistics and Transportation Review* 47, 1126-1139.

Ramirez-Rios, D.G., Kalahasthi, L.K., Holguín-Veras, J. (2023) On-street parking for freight, services, and e-commerce traffic in US cities: A simulation model incorporating demand and duration. *Transportation Research Part A: Policy and Practice* 169.

Rowell, M., Gagliano, A., Goodchild, A. (2014) Identifying truck route choice priorities: the implications for travel models. *Transportation Letters* 6, 98-106.

Sarti, L., Bravi, L., Sambo, F., Taccari, L., Simoncini, M., Salti, S., Lori, A. (2017) Stop Purpose Classification from GPS Data of Commercial Vehicle Fleets. *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*, pp. 280-287.

Sharma, S., van Lint, H., Tavasszy, L., Snelder, M. (2022) Estimating Route Choice Characteristics of Truck Drivers from Sparse Automated Vehicle Identification Data through Data Fusion and Bi-

Objective Optimization. *Transportation Research Record: Journal of the Transportation Research Board* 2676, 280-292.

Shoman, W., Yeh, S., Sprei, F., Köhler, J., Plötz, P., Todorov, Y., Rantala, S., Speth, D. (2023) A Review of Big Data in Road Freight Transport Modeling: Gaps and Potentials. *Data Science for Transportation* 5.

Sun, Y., Toledo, T., Rosa, K., Ben-Akiva, M.E., Flanagan, K., Sanchez, R., Spissu, E. (2013) Route Choice Characteristics for Truckers. *Transportation Research Record: Journal of the Transportation Research Board* 2354, 115-121.

Tao, X., Zhu, L. (2020) Meta-analysis of value of time in freight transportation: A comprehensive review based on discrete choice models. *Transportation Research Part A: Policy and Practice* 138, 213-233.

Toledo, T., Atasoy, B., Jing, P., Ding-Mastera, J., Santos, J.O., Ben-Akiva, M. (2020) Intercity truck route choices incorporating toll road alternatives using enhanced GPS data. *Transportmetrica A: Transport Science* 16, 654-675.

Toledo, T., Sun, Y., Rosa, K., Ben-Akiva, M., Flanagan, K., Sanchez, R., Spissu, E. (2013) Decision-Making Process and Factors Affecting Truck Routing. *Freight Transport Modelling*, pp. 233-249.

Tsirimpa, A., Polydoropoulou, A., Tsouros, I. (2019) Route choice preferences: insights from Portuguese freight forwarders and truck drivers. *Transportation Planning and Technology* 42, 729-738.

Wang, X., Zhang, D. (2017) Truck freight demand elasticity with respect to tolls in New York State. *Transportation Research Part A: Policy and Practice* 101, 51-60.

Wang, Z., Goodchild, A.V. (2014) GPS Data Analysis of the Impact of Tolling on Truck Speed and Routing. *Transportation Research Record: Journal of the Transportation Research Board* 2411, 112-119.

Wood, H.P. (2012) *Truck Tolling: Understanding Industry Tradeoffs When Using or Avoiding Toll Facilities*.

Xu, H., Yang, H., Zhou, J., Yin, Y. (2017) A route choice model with context-dependent value of time. *Transportation Science* 51, 536-548.

Yamamoto, T., Takamura, S., Morikawa, T. (2018) Structured random walk parameter for heterogeneity in trip distance on modeling pedestrian route choice behavior at downtown area. *Travel Behaviour and Society* 11, 93-100.

Yang, C., Chen, M., Yuan, Q. (2021a) The geography of freight-related accidents in the era of E-commerce: Evidence from the Los Angeles metropolitan area. *Journal of Transport Geography* 92.

Yang, X., Sun, Z., Ban, X.J., Holguín-Veras, J. (2014) Urban Freight Delivery Stop Identification with GPS Data. *Transportation Research Record: Journal of the Transportation Research Board* 2411, 55-61.

Yang, Y., Jia, B., Yan, X.-Y., Li, J., Yang, Z., Gao, Z. (2022a) Identifying intercity freight trip ends of heavy trucks from GPS data. *Transportation Research Part E: Logistics and Transportation Review* 157.

Yang, Z., Chen, X., Pan, R., Yuan, Q. (2022b) Exploring location factors of logistics facilities from a spatiotemporal perspective: A case study from Shanghai. *Journal of Transport Geography* 100, 103318.

Yu, C., Deng, Y., Qin, Z., Yang, C., Yuan, Q. (2023) Traffic volume and road network structure: Revealing transportation-related factors on PM2.5 concentrations. *Transportation Research Part D: Transport and Environment* 124.

Yu, C., Hua, W., Yang, C., Fang, S., Li, Y., Yuan, Q. (2024) From sky to road: Incorporating the satellite imagery into analysis of freight truck-related crash factors. *Accid Anal Prev* 200, 107491.

Yuan, Q., Wang, J. (2021) Goods movement, road safety, and spatial inequity: Evaluating freight-related crashes in low-income or minority neighborhoods. *Journal of Transport Geography* 96.

Zhou, L., Burris, M.W., Baker, R.T., Geiselbrecht, T. (2009) Impact of Incentives on Toll Road Use by Trucks. *Transportation Research Record: Journal of the Transportation Research Board* 2115, 84-93.

Zhu, S., Bell, M.G., Schulz, V., Stokoe, M. (2023) Co-modality in city logistics: Sounds good, but how? *Transportation Research Part A: Policy and Practice* 168, 103578.