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Uncovering heterogeneous decision-making in truck tour organization: A shipment-based behavioral modeling approach

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ABSTRACT

The efficient movement of freight trucks is vital for modern logistics, where the organization of truck tours is central to optimizing supply chain operations and minimizing transportation costs. The truck tour patterns embody a complex interplay of diverse decision-making factors, reflecting the effectiveness of transport and logistics planning initiatives. Despite previous research efforts, an in-depth analysis of understanding how various decision-making factors, such as time of the day and product type, interact and their heterogeneous effects on shaping truck tour patterns is still lacking. This limitation hinders the development of more effective and sustainable strategies for freight transportation. In this paper, by leveraging large-scale carrier and shipment dataset in the Netherlands, we capture and analyze the heterogeneity of over 1000 diverse tour patterns of freight trucks in terms of temporal, spatial, and shipment requirements characteristics. We further introduce a novel modeling approach using random parameters logit models with heterogeneity in means and variances to uncover the heterogeneous effects of various factors on the choice of truck tour patterns. The model results highlight the multifaceted nature of truck travel behaviors, offering practical implications for logistics operations, policy development and freight planning.

1. Introduction

The movement of freight trucks is a fundamental component of modern logistics and supply chain operations, playing a crucial role in the efficient transportation of goods (Tavasszy and de Bok, 2023). In an era of globalization and interconnected markets, the seamless flow of products from manufacturers to consumers relies heavily on the reliability and efficiency of freight truck operations (Jia et al., 2023; Lin et al., 2023; Yang et al., 2023a). The logistics activities of freight trucks are commonly organized as tours (Torkjazi et al., 2018), which include decisions regarding routes, timing of shipments, and handling various logistical complexities. These decisions go beyond mere geographical paths. They embody a complex interplay of decisions, considerations, and logistics strategies (Fugate et al., 2009). These decisions are influenced by numerous factors, such as heterogeneous cargo-specific requirements, nature of freight sectors, and traffic conditions. The complexity of these decisions has a profound impact on the economic efficiency and environmental sustainability of the transportation industry (Liu et al., 2019).

Understanding these heterogeneous factors is critical because truck tour decisions are inherently context-dependent—different stakeholders respond differently to the same conditions, and the same requirements may lead to varied tour patterns depending on temporal, spatial, and cargo-specific interactions (Yang et al., 2024a). Without capturing this heterogeneity, we risk developing ineffective one-size-fits-all strategies that ignore how various factors interact to shape actual decision-making. This understanding provides the foundation for targeted logistics optimization and evidence-based policy interventions,

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such as identifying which sectors are flexible for off-peak deliveries or which tour patterns are most sensitive to spatial constraints, ultimately enhancing operational efficiency and sustainability in freight transportation (Giduthuri, 2015).

Truck tours are a fundamental aspect of logistics and transportation operations (Ni and Wang, 2021), serving as a structured sequence of movements and activities for commercial trucks. They encompass a series of interconnected stops and movements, starting from a designated base location, which could be a distribution center, warehouse, or depot. The primary purpose of a truck tour is to efficiently manage the transportation of goods from one point to another, involving stops at intermediate locations to perform various tasks such as pickup and delivery activities. These tours play a pivotal role in optimizing supply chain operations (Ni and Wang, 2021), reducing transportation costs (Figliozzi, 2010), and ensuring timely and accurate goods distribution (van der Spoel et al., 2017). Each truck tour is unique, influenced by complex factors including geographical layout, traffic conditions, delivery schedules, and the nature of the goods being transported. Recognizing and analyzing these diverse tour patterns is essential for logistics professionals to make informed decisions that optimize the entire transportation process.

Traditionally, truck tours information has been obtained through manual surveys, which are time-consuming and often limited in data quantity, hindering comprehensive and in-depth analysis (Alho et al., 2018). Therefore, most previous studies of truck tour patterns are based on passively collected data, such as GPS trajectory data (Akter et al., 2023; Gingerich et al., 2016; Jia et al., 2025; Romano Alho et al., 2019; Yang et al., 2022a; You and Ritchie, 2018). This dataset offers insights into the actual routes taken by trucks, providing the possibility to study truck tour patterns across diverse geographical regions. GPS trajectory data, while a valuable source of information for understanding the movement of freight trucks, comes with its own set of limitations. It often lacks crucial cargo-specific information for each tour, which is fundamental in comprehending the complexities of freight activities. Truck tour organization is not solely determined by the physical route taken; it is also shaped by a wide array of factors, including temporal considerations, spatial constraints, and sector-specific requirements (Thoen et al., 2020). The lack of insight into the type and unique characteristics of the cargo being transported leaves a significant gap in our understanding of the decision-making factors influencing truck travel behavior.

To address the limitations of vehicle-based analysis, previous studies shift towards commodity-based analysis (Comi and Delle Site, 2023; de Bok and Tavasszy, 2018; Gonzalez-Calderon and Holguín-Veras, 2019; Holguin-Veras and Patil, 2007; Ruan et al., 2012; Teye and Hensher, 2021; Thoen et al., 2020), which sheds light on how different types of goods influence tour patterns. Commodity-based analysis emerges as a promising avenue to offer a more nuanced understanding of the intricate relationship between cargo specifics and truck tour patterns. However, there remains a substantial research gap in comprehensively understanding the heterogeneous decision-making factors that underlie the organization of truck tours. Truck tour organization is a complex interplay of various factors, including the type of cargo, spatial constraints, temporal considerations, and sector-specific requirements. These factors exhibit significant variations, both within and between different regions, and among different trucking companies (Chow et al., 2010). While previous studies have made strides in recognizing the importance of commodity-based analysis, there is still limited research that delves into the nuanced, heterogeneous effects of decision-making factors on the organization of truck tours.

In this paper, we employ a novel and comprehensive approach to bridge the existing research gaps in understanding the complex nature of truck tour organization. Leveraging a dataset comprising large-scale carrier and shipment data, we capture and analyze the heterogeneity of over 1000 diverse tour patterns of freight trucks in the Netherlands based on detailed cargo-specific information. We further introduce an innovative methodology using random parameters logit models with heterogeneity in means and variances, offering a deeper understanding of the heterogeneous effects of various factors on the organization of truck tour patterns. By combining large-scale carrier and shipment data with advanced modeling techniques, we aim to provide a holistic perspective on the multifaceted nature of truck travel behavior and logistics operations.

This study offers significant implications for multiple stakeholders. For policymakers and urban planners, understanding why certain tour patterns are chosen enables effective urban freight strategies. For example, identifying which sectors are flexible regarding delivery times can inform targeted off-peak delivery incentives, while understanding the spatial logic of sequential versus complex tours can guide infrastructure planning (e.g., urban consolidation centers, loading zones, freight lanes). For logistics operators, modeling heterogeneous effects provides operational efficiency benchmarks, helping them understand decision-making trade-offs, refine fleet management, and optimize routing for diverse shipment requirements. For researchers, moving beyond tour descriptions to modeling underlying behavioral choices provides a robust foundation for analyzing policy or technology impacts.

The contribution of our study to the literature is threefold, representing an integrated advance in data, methodology, and analytical focus that addresses critical gaps in freight transportation research.

(1) Empirical contribution: We capture and analyze over 1000 distinct freight tour patterns using a large-scale national dataset of over 4 million shipments with detailed cargo-specific information. This overcomes the critical limitation of previous research, which has relied on either GPS trajectory data lacking cargo details or smaller-scale surveys lacking operational comprehensiveness and statistical power.
(2) Methodological innovation: We introduce the Random Parameters Logit model with Heterogeneity in Means and Variances (RPLH) to freight tour pattern analysis. This represents its first application to freight tour organization, allowing us to move beyond conventional models' restrictive assumptions and capture how operator preferences and decision-making sensitivities vary systematically with shipment context.
(3) Analytical contribution: By integrating this advanced model with comprehensive shipment data, we shift from merely describing tour patterns to explicitly modeling underlying behavioral choices and their complex trade-offs. We uncover the heterogeneous and interactive effects of temporal, spatial, and shipment-specific factors on tour organization, providing a behaviorally realistic foundation for targeted policy interventions and logistics optimization.

The remainder of this paper is organized as follows: Section 2 gives the literature review. Section 3 presents the collection and details of carrier and shipment data. Section 4 provides the analysis of heterogeneity of truck tour patterns in terms of travel time, regions, and shipment requirements. Section 5 describes the construction of the random parameters logit model with heterogeneity in means and variances, and the empirical setting is shown in Section 6. Section 7 details the model results. Section 8 and Section 9, at the end, offer discussion and concluding insights.

2. Literature review

In the realm of logistics and freight transportation, understanding the formation and optimization of tour patterns for freight vehicles is a critical focus of research and practical application (Ehmke, 2012; Tavasszy et al., 2020). These tour patterns are integral to efficient goods movement and have far-reaching implications for supply chain management, cost-effectiveness, and environmental sustainability. Various factors, including delivery time, size, weight dimensions, destinations,

and specific delivery requirements, influence the complex decisions involved in organizing truck tours (de Bok et al., 2022; Khan and Machemehl, 2017). Consequently, an extensive body of literature has emerged, dedicated to modeling and optimizing the tour patterns of freight vehicles (Thoen et al., 2020).

Vehicle-based approaches (Akter et al., 2023; Demissie and Kattan, 2022; Doustmohammadi et al., 2016; Gingerich, 2017; Gingerich et al., 2015; Hou et al., 2019; Kinjarapu, 2018; Lv et al., 2024; Romano Alho et al., 2019; Yang et al., 2023b, 2024b, 2024c, 2025a; Yin et al., 2026; You, 2012; You and Ritchie, 2018, 2019) are a commonly employed technique that primarily focus on modeling and understanding the movements of individual freight trucks within a transportation network. Researchers have leveraged various data sources and analytical tools to delve into the specifics of how freight trucks traverse their routes and execute origin-to-destination trips (Nuzzolo et al., 2012). One of the key data sources frequently employed in vehicle-based approaches is GPS trajectory data (Gingerich et al., 2016; Yang et al., 2022a), which offers an extensive and granular dataset for scrutinizing the real-time movements of trucks. This information allows for a detailed analysis of the routes taken, travel times, stop locations, and other operational aspects, enabling researchers to gain insights into the intricacies of freight truck movements. Vehicle-based approaches provide a comprehensive understanding of individual truck operations, making them crucial for tasks such as route optimization (Mayerle et al., 2020), fleet management (Moradi Afrapoli and Askari-Nasab, 2019), and real-time tracking of freight vehicles. By analyzing the exact paths taken by trucks and the specific stops they make, researchers can gain a comprehensive view of the transportation process, helping to optimize delivery schedules, enhance fleet efficiency, and improve overall supply chain management (Soares et al., 2019; Wang et al., 2018). However, vehicle-based approaches do have their limitations, particularly when it comes to analyzing complex tour patterns that involve multiple stops and a diverse array of origins contributing to a single tour (Alho et al., 2021). While they are effective at capturing the details of individual trips, they may also fall short in providing a comprehensive understanding of how cargo specifics, temporal considerations, and sector-specific requirements influence tour organization (Kim and Park, 2017).

To address the limitations of vehicle-based approach, commodity-based approaches (Aguas, 2021; Alho et al., 2017; Boerkamps et al., 2000; Chandra et al., 2023; Chow et al., 2010; Comi and Delle Site, 2023; Dabbagh, 2022; de Bok and Tavasszy, 2018; Gonzalez-Calderon and Holguín-Veras, 2019; Holguin-Veras and Patil, 2007; Murshed, 2018; Ruan et al., 2012; Teye and Hensher, 2019, 2021; Thoen et al., 2020), on the other hand, offer a discerning viewpoint by focusing on the goods being transported rather than individual vehicle movements (Wisetjindawat et al., 2007). These methods delve into the characteristics of the cargo, including its type, size, weight, perishability, and specific handling requirements. This approach recognizes that the organization of truck tours is not solely determined by the physical routes taken but is significantly shaped by the nature of the freight being carried. The data sources for commodity-based studies vary considerably. Some researchers use shipper surveys (Holguin-Veras and Patil, 2007; Ruan et al., 2012), which provide detailed information about shipment characteristics (commodity type, size, origin-destination) but are often limited in sample size (typically hundreds to a few thousand observations) and subject to response bias. Others utilize commercial datasets from logistics service providers (de Bok and Tavasszy, 2018; Thoen et al., 2020) or administrative freight flow databases (Boerkamps et al., 2000; Teye and Hensher, 2021), offering larger sample sizes but sometimes lacking operational details like actual routes or timing.

Beyond data sources, the choice of mathematical framework is equally critical in the literature. Entropy Maximization (EM) has historically served as a foundational tool for modeling freight flows and tour formations, particularly in aggregate analyses (Jaynes, 1957; Lopez-Ospina et al., 2025; Moreno-Palacio et al., 2024). By identifying the most probable distribution state subject to known constraints (e.g., traffic counts or average trip lengths), EM provides a robust framework for reproducing macroscopic flow patterns. However, while EM models excel at aggregate estimation, they are theoretically less suited for analyzing the specific behavioral trade-offs and preference heterogeneity of individual freight operators. As a result, research aiming to capture the complex, disaggregate decision-making processes underlying tour organization typically necessitates alternative modeling frameworks.

Methodologically, commodity-based studies predominantly employ discrete choice models to analyze freight-related decisions. For instance, Ravibabu (2013) used a nested logit model with rail container and road truck in one branch to predict the mode choice behavior leveraging a structured questionnaire from 124 export firms. Piendl et al. (2017) developed a logit-based discrete shipment size choice model for truck transports on the basis of discretized total logistics cost using revealed preference data from 487 German enterprises. Ahmed and Roorda (2022) advanced the field by implementing mixed logit (random parameters logit, RPL) model to analyze freight vehicle type choices using commercial travel surveys. A critical limitation across these commodity-based studies is the methodological assumption of either no heterogeneity (fixed-parameter models) or homogeneous heterogeneity (standard RPL models). While standard RPL models represent an important advancement by acknowledging that different decision-makers have different preferences, they assume that the average preference is the same across all observations and that the variability in preferences is constant. This overlooks the reality that preferences may systematically vary based on observable characteristics.

Recent advances in discrete choice modeling have introduced random parameters models with heterogeneity in means and variances (RPLH) (Fiebig et al., 2010), which allow both the average preference and the degree of preference variability to depend on observable factors. These models have been successfully applied in passenger transportation (Behnood et al., 2022; Mannering et al., 2016), but have not been applied to freight tour pattern analysis. This methodological gap is significant because freight decisions are inherently context-dependent, shaped by interactions between temporal constraints, spatial factors, and cargo-specific requirements, interactions that cannot be captured by models assuming homogeneous distributions.

In summary, while prior research has devoted considerable effort to understanding truck tour organization, three interconnected gaps remain. First, methodologically, existing studies rely on either fixed-parameter models or standard RPL models with homogeneous distributional assumptions, which cannot capture how preference heterogeneity systematically varies with contextual factors. Second, empirically, previous studies use either vehicle-tracking data without cargo information or shipment data with limited temporal-spatial context, but rarely integrate comprehensive information across all dimensions. Third, analytically, limited research examines the interactive and conditional effects of multiple factors on tour organization, how temporal, spatial, and cargo-specific factors combine to influence decisions.

Our study addresses these three gaps simultaneously by: (1) applying an advanced model RPLH to freight tour analysis—allowing heterogeneity in both means and variances; (2) leveraging an integrated dataset of over 4 million shipments with detailed cargo, temporal, spatial, and agent information; and (3) systematically analyzing how decision-making factors interact to shape over 1000 distinct tour patterns. This integrated approach represents a significant advancement over previous freight transportation research and provides the analytical foundation for evidence-based policy development.

3. Data

In this research, we utilized an extensive and distinctive dataset of truck diaries provided by Statistics Netherlands, also known as the Centraal Bureau voor de Statistiek (CBS). This dataset comprises a total

of over 4 million digitally collected records pertaining to shipments reported by Dutch companies in the year of 2015. In this context, each record represents a single shipment—that is, the movement of a specific quantity of goods from one loading location to one unloading location. The data is not based on GPS tracking but is derived from company-reported truck diaries that are digitally collected by CBS as part of a mandatory national survey. In the Netherlands, companies are obliged to report on their shipments per vehicle which allows high volumes of data with high density. CBS keeps track of shipments carried by trucks with a capacity of at least 3.5 metric tons. Each entry in this dataset includes crucial shipment details, including geographic information concerning loading and unloading locations, types of commodities transported, and vehicle characteristics including vehicle class (e.g., light vs. heavy trucks based on loading capacity) and vehicle identification number. By employing a data fusion approach (refer to the work done by Mohammed et al. (2023)), we further enriched the attributes of pickup and delivery locations of the shipments. Specifically, we integrated the CBS shipment data with the Dutch business register, which contains comprehensive information about all registered business establishments in the Netherlands. This fusion process matched the geographic coordinates of loading and unloading locations in the shipment data with corresponding business establishments in the register, enabling us to identify the freight agent type (e.g., whether a location functions as a producer/consumer, distribution center, or transshipment terminal) and the economic sector (e.g., manufacturing, wholesale, retail) associated with each shipment origin and destination.

The enriched attributes include the information on freight agents and sectors associated with locations. Specifically, there are three types of freight agents, i.e., producer or consumer (P/C), distribution center (DC) and transshipment terminal (TT). Fourteen aggregate sectors are identified: manufacturing-nonfood, manufacturing-food, wholesale, agriculture, horeca, storage and transport, auto heavy machinery, construction, retail, raw materials, utility, chemicals, waste management and minerals.

Leveraging the large-scale carrier and shipment data, we can obtain the tour information of freight trucks, as well as the trip purposes, as shown in Fig. 1. A truck tour is characterized as a trip chain or sequence, in which the truck starts from a base location, visits one or more intermediate locations for different purposes (e.g., pickup/delivery), and finally returns to its base location. The cargo-specific and vehicle-specific information is integrated in our analysis to explore truck tour patterns and travel behaviors.

4. Heterogeneity of tour patterns of freight trucks

Here we first extract various tour patterns from the obtained truck tours, and then explore the heterogeneity of different tour patterns in terms of travel time, regions, and shipment requirements.

4.1. Tour patterns

We extract tour patterns according to the structured format of all truck tours. A tour can be viewed as a truck mobility network, in which nodes represent base and intermediate locations visited by a truck, links represent directed trips between locations. A tour pattern is a representation of tours with the same network topology. We first obtain the network topology of each tour, and then classify it to the corresponding tour pattern. In the end, we extract over 1000 unique tour patterns of trucks, and the top 10 typical tour patterns with the highest proportions, as shown in Fig. 2.

The results show that trucks make the highest percentage of tours between two locations, i.e., direct tours. This tour pattern can be more cost-effective for certain shipments. By avoiding intermediate stops, trucks can reach their destinations faster and complete more tours within a given timeframe. This efficiency can be crucial for time-sensitive deliveries or when minimizing transit times is a priority (Jin et al., 2013). In addition to this tour pattern, trucks tend to visit many intermediate locations in sequence and return to their base location, i.e., sequential tours. Trucks may need to visit intermediate locations to pick up or deliver goods at various stages of the supply chain, such as

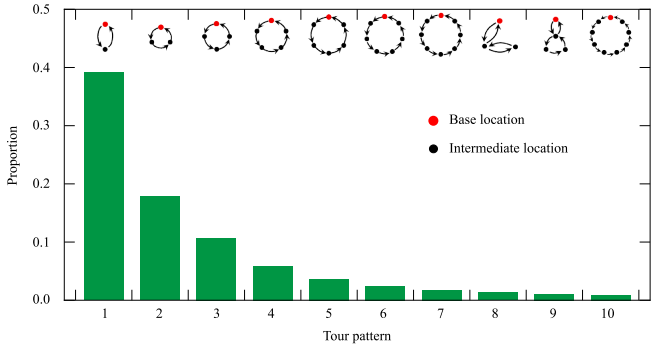


Fig. 2. The proportion of 10 typical truck tour patterns. The top 10 graphs show the typical tour patterns.

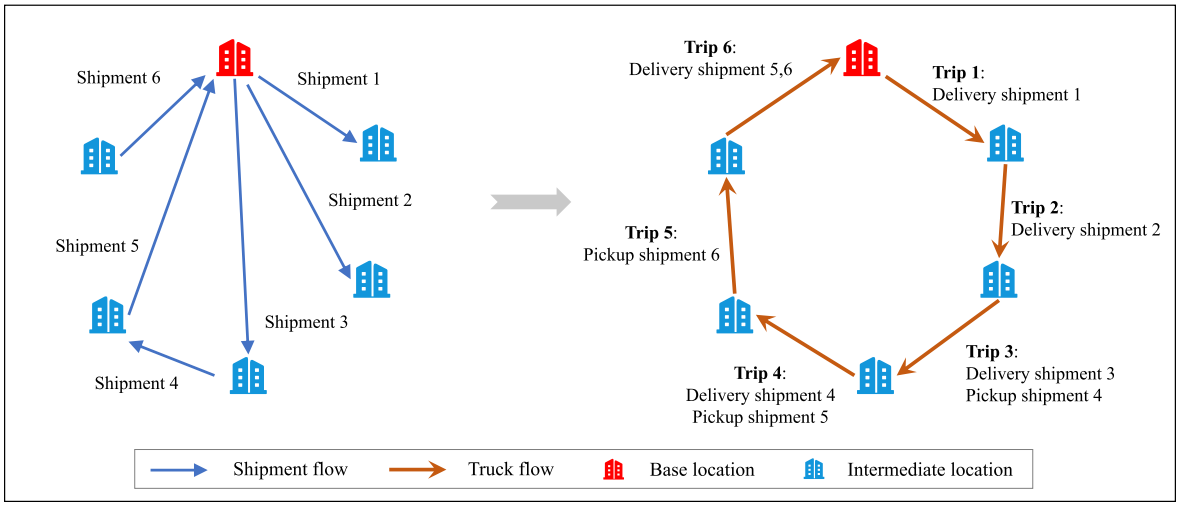


Fig. 1. Illustration of converting shipments to truck tours.

warehouses, distribution centers or retail stores, facilitating the movement of goods along the supply chain efficiently (Chen et al., 2023; Holzapfel et al., 2023). We can also observe that some trucks visit specific intermediate locations several times during their tours, and we refer to these tours as the complex tours. In such a pattern, specific intermediate locations act as hubs or central points where goods are consolidated, sorted, or distributed. The descriptive statistics of three types of tour patterns, i.e., direct tour (type I), sequential tour (type II) and complex tour (type III) are shown in Table 1.

The results show that sequential tours have the highest proportion, and the proportion of different sequential tour patterns decreases with an increase in the number of intermediate locations. These types of tours are followed by the direct tours that indicate widespread preference for direct tours. The proportion of complex tours is the lowest, but they include over 1000 different tour patterns, highlighting the complexity and diversity of truck tour patterns.

4.2. Travel times

Next, we uncover the heterogeneity of different types of tour patterns in terms of travel time, regions, and shipment structure, aiming to understand how these diverse tour patterns meet specific logistics needs.

To begin with, we explore the heterogeneity of truck travel times across different types of tour patterns. We calculate the departure days of week and times of day for all truck tours and obtain the corresponding distributions for three types of tour patterns, as shown in Fig. 3. The results indicate that the proportion of truck freight activities during weekdays (i.e., from Monday to Friday) is significantly higher than that during weekends (i.e., from Saturday to Sunday). Specifically, trucks are more likely to make direct tours on weekends compared to sequential and complex tours (see Fig. 3a). For the observations of departure times of day, we can find that most sequential tours and complex tours depart in the early morning (around 5am), while a higher proportion of direct tours depart at midday (around 12am), as shown in Fig. 3b. Early morning departures allow trucks to take advantage of lighter traffic conditions, reducing the risk of delays and congestion. On the other hand, midday departures for direct tours can be advantageous in terms of customer convenience, as they allow deliveries to be made during standard business hours when receivers are staffed and available to accept shipments (Tootkaleh et al., 2016).

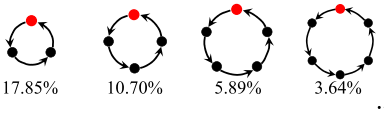
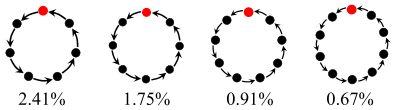
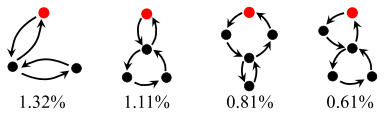
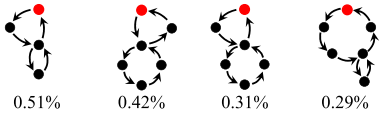
4.3. Travel regions

In addition to truck departure time, the geographic distribution of pickup and delivery points in different regions is also a crucial factor in determining trucking operations (Chen et al., 2021; Teo et al., 2015), as it affects travel distance and cost, as well as delivery time. Here we explore the heterogeneity of truck travel regions across different types of tours. In the carrier and shipment database, all shipments between regions, encoded by 6-byte postcodes (e.g., 2600AA) according to national geographical divisions in the Netherlands, can be acquired. There are more than 400,000 regions throughout the country. The freight demand of a specific region is defined by the sum of the quantities of all shipments in the database moving in and out of this region.

First, we calculate the average freight demand of the regions where the truck visits during each tour, and the distributions are shown in Fig. 4a. The results suggest that the distribution of direct tours in regions of low freight demand is more prevalent, and sequential tours are utilized to a lesser extent, while complex tours are typically reserved for regions with higher freight demand. Regions with low freight demand typically have a smaller number of delivery points. This simplifies the logistics process, allowing trucking companies to efficiently plan and execute direct tours. In contrast, complex tours allow for efficient consolidation and delivery of goods to multiple destinations within these regions, catering to the diverse needs of the market.

Second, we analyze how the traffic conditions can affect the organization of truck tours. We make use of vehicle speed data derived from loop detectors to obtain congestion information for the pickup and delivery locations, and more details can be found in the recent work (Nadi et al., 2022). We use the same method introduced by Christidis and Rivas (2012) to obtain the aggregate congestion level for each region. Fig. 4b shows the distributions of average delay time of truck visited regions for three types of tours. The results suggest that trucks tend to visit regions with low congestion levels in direct tours, as opposed to

Table 1
Descriptive statistics of truck tour patterns. We classify the truck tour patterns into three types (I, II, III) as shown in the first column. The number of tour patterns and proportion of truck tours included in type I-III are shown in the second and third columns. The last column indicates some of the most frequently observed tour patterns, and their proportions are placed under the graphs.

Classification of tour patterns	Number of tour patterns	Proportion of truck tours	Typical tour patterns and proportions
Type I: Direct tour	1	39.14 %	39.14%
Type II: Sequential tour	27	46.37 %	 17.85% 10.70% 5.89% 3.64% … …  2.41% 1.75% 0.91% 0.67%
Type III: Complex tour	1315	14.49 %	 1.32% 1.11% 0.81% 0.61% … …  0.51% 0.42% 0.31% 0.29%

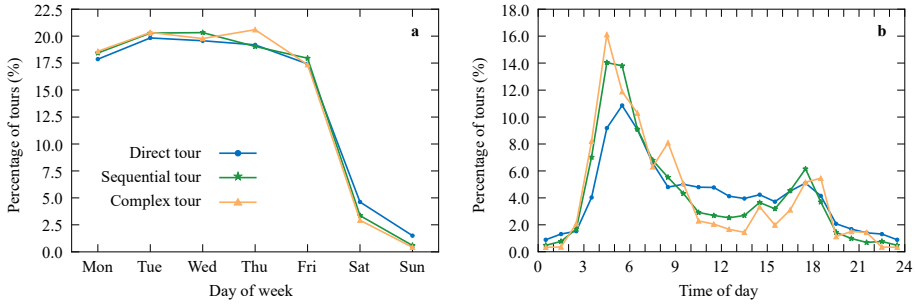


Fig. 3. Distributions of departure times for three types of tour patterns. **a** Departure day of week. **b** Departure time of day.

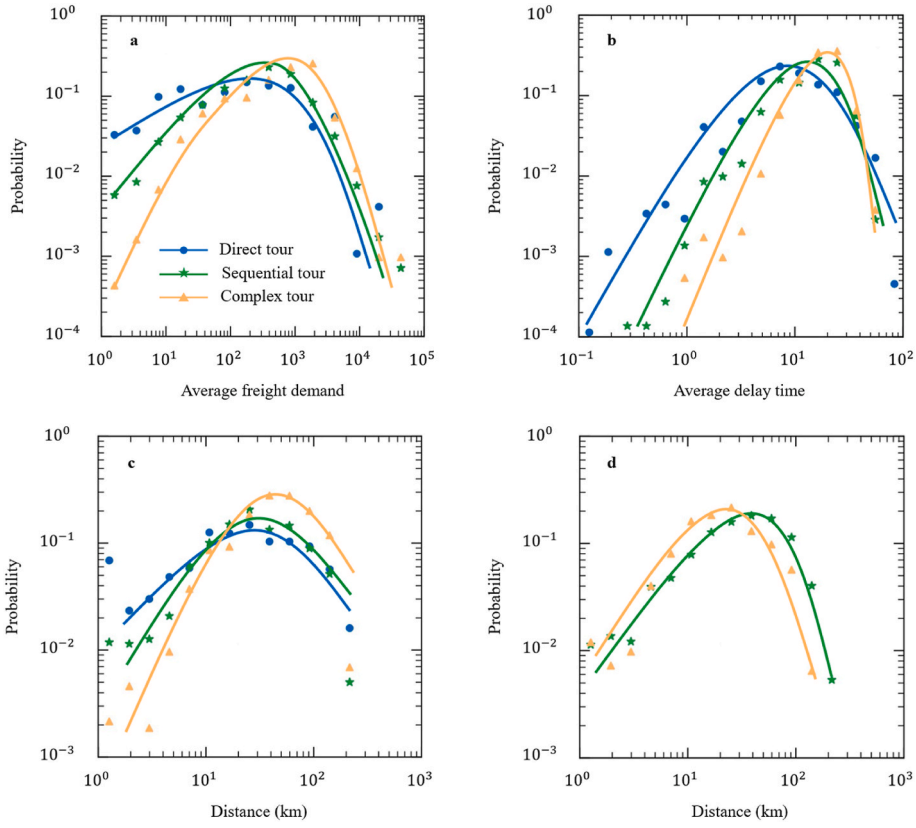


Fig. 4. Distributions of the spatial features of tour pathway regions for three types of tour patterns. **a** Average freight demand. **b** Average delay time. **c** Average distance from base location to all intermediate locations. **d** Average distance between all intermediate locations. Note that a direct tour has only one intermediate location, so there is no data distribution for direct tours in the figure. For simplicity and clarity, the data are distributed in logarithmic bins in all panels, i.e., the values on the horizontal axis are placed in bins that are evenly spaced on a logarithmic scale. Each line represents the fitted distribution for each type of tour patterns.

sequential tours and complex tours.

Third, we explore the spatial operational characteristics of the three tour types to distinguish between short-haul and long-haul patterns. For each truck tour, we calculate two key metrics: the average distance from the base location to all intermediate locations (representing the radius of operation) and the average distance between these intermediate locations (representing stop density). Fig. 4c presents the distribution of distances from the base location. The results reveal a clear operational distinction: direct tours predominantly serve short-distance, short-haul transport needs, keeping close to the base. In contrast, complex and sequential tours exhibit long-haul characteristics, with intermediate locations situated significantly farther from the base. However, a further distinction emerges when analyzing the distance between intermediate stops (Fig. 4d). Sequential tours are characterized by dispersed stops (large inter-stop distances), indicative of regional or inter-regional long-haul distribution. Conversely, complex tours show a unique hybrid pattern: while they travel long distances from the base (long-haul stem), their intermediate stops are highly concentrated (small inter-stop distances). This suggests a distinct logistics pattern where heavy vehicles perform a long-haul line haul followed by intensive local distribution in a specific urban or industrial area.

4.4. Shipment requirements

Next, we investigate how truck tours are designed to meet the specific shipment requirements of different freight agents and industries. The carrier and shipment database provides detailed cargo-specific information for each truck tour. We first focus on two shipment structures, i.e., consecutive and consolidated shipments. Consecutive shipments refer to a series of individual shipments that are arranged in sequence, i.e., the destination of a previous shipment is the origin of the next shipment. Consolidated shipments involve combining multiple

individual shipments from different origins to a destination, or from an origin to different destinations. For each truck tour, we examine whether there are consecutive and consolidated shipments in the tour, and obtain the percentages for three types of tours, as shown in Fig. 5. The results suggest that 57.34 % of the direct tours only involve one-way transport of goods from the base location to the intermediate location (see Fig. 5a). The remaining 42.66 % of direct tours involve consecutive shipments, meaning the truck performs both a pickup and a delivery at the same intermediate location within a single tour. For example, delivering goods from the base to the intermediate location and subsequently picking up different goods from that same location to return to the base. This creates a round-trip tour where both legs carry cargo. In contrast, a higher proportion of sequential tours or complex tours are likely to involve consecutive shipments. Additionally, the proportions of complex tours involving either consecutive shipments (see Fig. 5a) or consolidated shipments (see Fig. 5b) are higher than that of sequential tours.

Then, we analyze the freight agents served in three types of tours. There are three types of freight agents, i.e., TT, DC and P/C. For each truck tour, we examine whether a specific freight agent is visited by this truck in the tour, and calculate the percentages for three types of tours, as shown in Fig. 6. The results indicate that, compared to direct tours and sequential tours, the proportion of complex tours involving either TT, DC, or P/C is the highest. Complex tours often involve value-added services such as consolidating, sorting and redistributing goods, which are efficiently carried out at transshipment terminals or distribution centers that commonly serve as hub points.

Then, we analyze the freight sectors or industries served in three types of tours. As we mentioned in Section 3, we identify fourteen aggregate sectors. For each truck tour, we obtain the freight sectors involved in this tour according to the categories of commodities being transported. We calculate the percentage of the three types of tours that serve each freight sector, as shown in Fig. 7. The results suggest that the freight sectors involved in different tours are heterogeneous. Truck direct tours account for a higher proportion for the manufacturing-food and chemicals sectors compared to other sectors, but a lower proportion for raw materials and minerals sectors. This could be attributed to the specific nature of the products or supply chain complexity for each sector (Manuj and Sahin, 2011; Serdarasan, 2013).

5. Random parameters logit model with heterogeneity in means and variances

The empirical results in the above sections reveal the heterogeneity of different tour patterns in terms of travel time, regions, and shipment requirements. Here we use an innovative model, i.e., random parameters logit model with heterogeneity in means and variances (RPLH model) (Behnood et al., 2022; Mannering et al., 2016; Song et al., 2025; Wang et al., 2024), to quantify the influence of various factors on decision-making in the organization of three types of tours and understand how they interact to shape the final decisions, as shown in Fig. 8. While RPLH models have been successfully applied in passenger transportation research, their application to freight truck tour pattern analysis represents a methodological advance, as this approach allows us to capture context-dependent heterogeneity in freight decision-making that cannot be revealed by conventional discrete choice models.

Individual-level heterogeneity in the organization of different tours in the trucking industry arises due to various operational constraints. For example, two truck drivers facing the same set of factors (distance, time, cost, delivery requirements, etc.) may prioritize these factors differently based on their unique operational considerations. One driver may prioritize minimizing costs, while another one may prioritize minimizing travel time. This heterogeneity in priorities can lead to different choices in tour organization, such as one preferring direct tour while the other preferring sequential tour. To capture the individual-level heterogeneity, the random parameters logit (RPL) model, also referred to as the mixed logit model (Hensher and Greene, 2003; McFadden and Train, 2000), is one of the most commonly used approaches. In this model, individuals have the same average preferences, and the level of variability in their preferences is also constant. To obtain a more comprehensive analysis of decision-making behavior, we extend the RPL model by allowing the average preference (characterized by the mean of chosen distribution) to vary across individuals based on certain explanatory variables. The extended model is named RPLH model:

The function P_{ik} that determines the likelihood that tour type k will be organized to meet the shipment demand i is defined as

$$P_{ik} = \boldsymbol{\beta}_k \boldsymbol{X}_{ik} + \varepsilon_{ik}, \tag{1}$$

where $\boldsymbol{X}_{ik}$ is a vector of explanatory variables that affect the likelihood of tour type k being organized, $\boldsymbol{\beta}_k$ is a vector of estimable parameters for tour type k, and ε_{ik} is an error term which is assumed to follow an independent and identically distributed extreme value. The model allows estimable parameters $\boldsymbol{\beta}_k$ to vary across individuals, given by

$$\boldsymbol{\beta}_k = \boldsymbol{b}_k + \boldsymbol{\Theta}_k \boldsymbol{z}_{ik} + \boldsymbol{C}_k \boldsymbol{\varphi}_{ik}, \tag{2}$$

where $\boldsymbol{b}_k$ is the vector of mean parameter estimate across all individuals. If $\boldsymbol{\beta}_k = \boldsymbol{b}_k \; \forall \, i$, this implies no individual-specific unobserved heterogeneity, and the resulting model form is the standard multinomial logit (MNL) model; otherwise, some elements of $\boldsymbol{\beta}_k$ are assumed to be drawn from a distribution (e.g., normal distribution) with continuous density function $\text{Prob}(\boldsymbol{\beta}_k = \boldsymbol{\beta}) = f(\boldsymbol{\beta}|\boldsymbol{\varphi})$, where $\boldsymbol{\varphi}$ is a vector of the parameters characterizing the chosen density function (such as mean and variance). $\boldsymbol{z}_{ik}$ and $\boldsymbol{\varphi}_{ik}$ are vectors of explanatory variables from observation i that influence the mean and variance of the distribution respectively, $\boldsymbol{\Theta}_k$ and $\boldsymbol{C}_k$ are corresponding matrixes of estimable parameters. If there are no explanatory variables affecting the average preferences and the level of variability in preferences of individuals, and the resulting model form is the RPL model.

The probability of tour type k being organized is

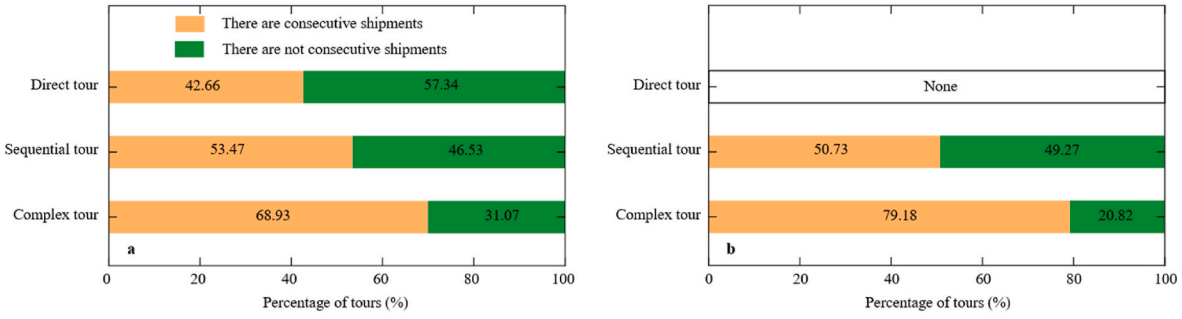


Fig. 5. Shipment structures in three types of tours. **a** Whether or not there are consecutive shipments in a truck tour. The number inside a bar indicates the percentage. **b** Whether or not there are consolidated shipments in a truck tour.

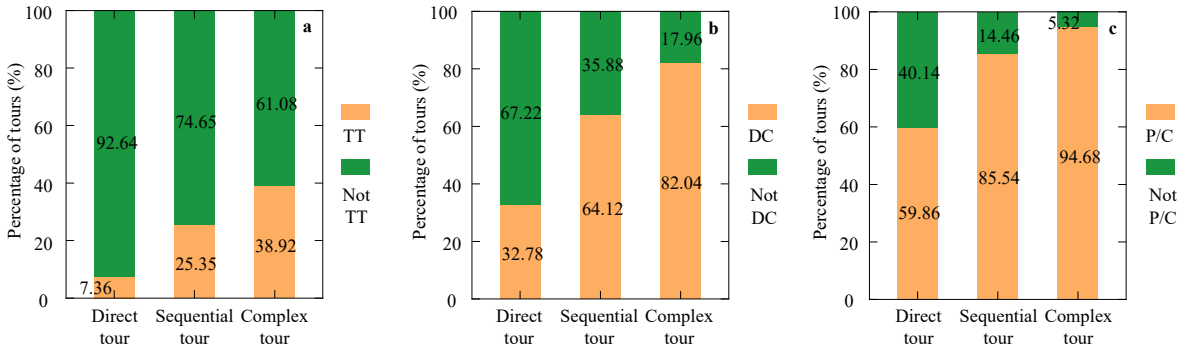


Fig. 6. Freight agents served in three types of tours. **a** Whether or not a transshipment terminal (TT) is visited by a truck in its tour. The number inside a bar indicates the percentage. **b** Whether or not a distribution center (DC) is visited by a truck in its tour. **c** Whether or not a producer or consumer (P/C) is visited by a truck in its tour.

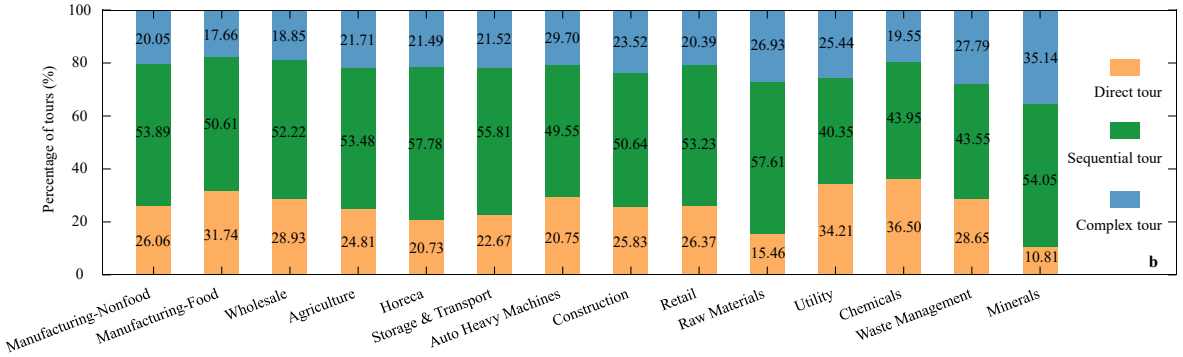


Fig. 7. Fourteen freight sectors served in three types of tours. The number inside a bar indicates the percentage.

$$P_i(k) = \int \frac{\exp(\boldsymbol{\beta}_k \boldsymbol{X}_{ik})}{\sum_m \exp(\boldsymbol{\beta}_k \boldsymbol{X}_{mk})} f(\boldsymbol{\beta}|\boldsymbol{\varphi}) \mathrm{d}\boldsymbol{\beta}. \tag{3}$$

In the model, some elements of the vector $\boldsymbol{\beta}_k$ can be fixed across individuals and some may vary across individuals. If the parameters do vary across individuals, then these parameters are referred to as random parameters, reflecting the heterogeneity in individual preferences. It is important to note that there are no alternative-specific variables intrinsic to tour types, only individual-specific variables related to each shipment demand. Therefore, we separate likelihood functions P_{ik} for each type of tour k, capturing the factors and considerations specific to its corresponding truck tour type.

In this study, model estimation is undertaken by using the Halton sampling method (Halton, 1964). To achieve a trade-off between the estimation performance and computation time, the simulated maximum likelihood approach with 1000 Halton draws is utilized. We consider several distributional forms (including normal, lognormal, triangular, and uniform distributions) for random parameters. The estimated results revealed that normal distribution resulted in a better statistical fit compared to others. To better interpret the estimated results, pseudo-elasticities (Washington et al., 2020) that represent the percentage change in the probability of a choice outcome for a one-unit change in the independent variable are computed. As reported in studies (Song et al., 2023a, 2023b; Su et al., 2023), pseudo-elasticities can provide a robust and accurate measure of the responsiveness of the dependent variable.

6. Empirical setting

The carrier and shipment, and firm databases provide detailed information on shipment demands met by truck tours. For each truck tour, we calculate its shipment-specific explanatory variables, including temporal, spatial and shipment requirements variables. The descriptive statistics of the explanatory variables are given in Table 2.

The temporal variables describe when the first shipment starts in different aspects, such as weekdays versus weekends, and specific time periods throughout the day. The spatial variables capture the characteristics of regions that pickup and delivery points located. These characteristics are related to the region freight demands, congestion levels and point spatial distances (see Section 4.3 for variable calculation). For the sake of interpretability, we categorize the spatial variables into three levels (i.e., low, medium and high) by using a nonparametric data classification method, named the Loubar method (Bassolas et al., 2019; Louail et al., 2014; Yang et al., 2022a). For example, to categorize the levels of region freight demand, we first obtain the freight demands of all regions encoded by 6-byte postcodes in Netherlands from the databases (see details in Section 4.3), and then use Loubar method to categorize this numeric variable into three levels, i.e., low, medium and high demand. The shipment requirements variables provide information about different conditions and factors associated with shipments, including shipment structures, freight agents and sectors involved.

7. Model results and analysis

Model estimation results for the organization of truck tours are given in Table 3. Overall, the estimation results show plausible parameter sign and excellent overall model fit with ρ^2 values exceeding 0.35. Due to the wide range of potential factors and many unknown factors affecting the likelihood of truck tours being organized, the overall model fits seem reasonable. The results show that considerable differences exist between the models estimated for different tour types. It is important to note that we define three likelihood functions for three tour types. The categories of variables inside likelihood functions are the same, but the corresponding coefficients in different likelihood functions are different. The

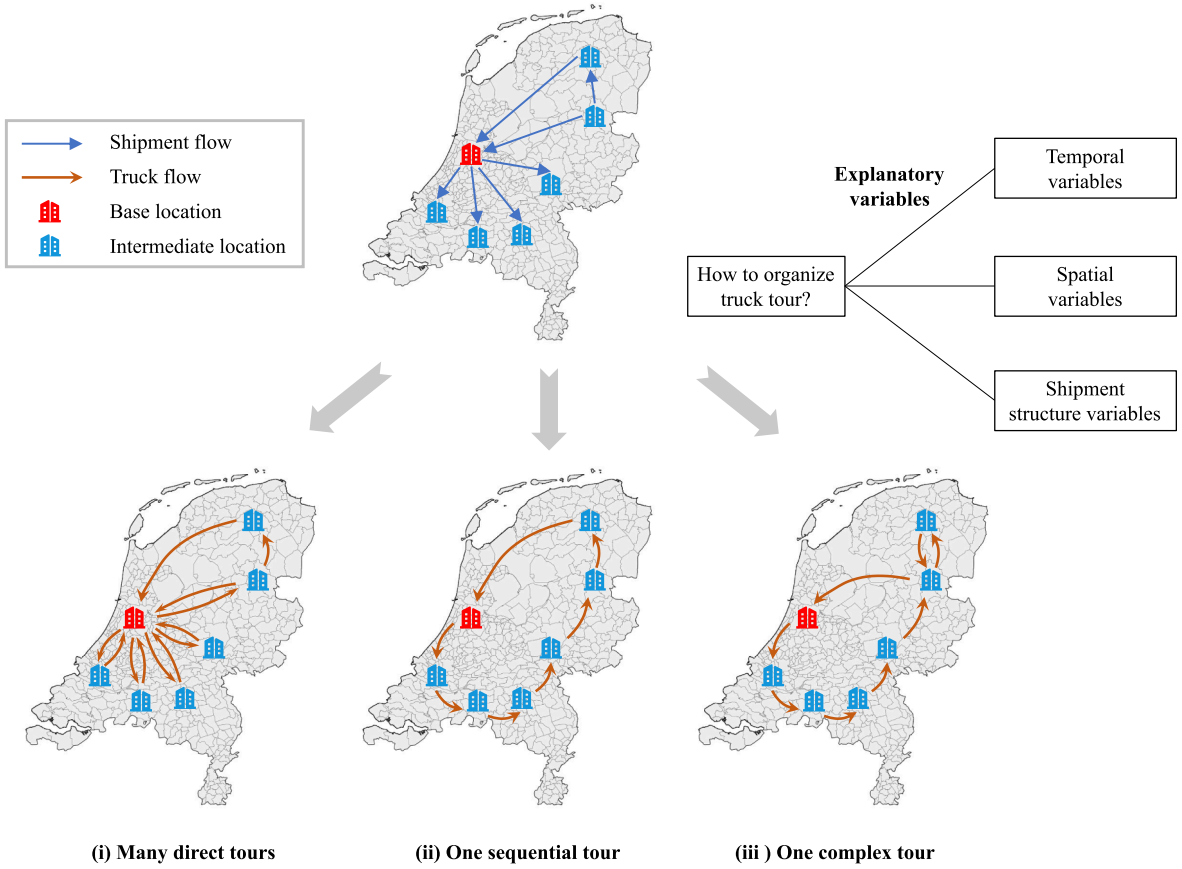


Fig. 8. Illustration of the framework for modelling heterogeneous decision making of tour types. The shipment flows between different locations are assumed to be first given, as shown in the top panel. We aim to uncover how different truck tours are organized (see the three tour type illustrations in the lower panels) to meet the given shipment flows by using three categories of explanatory variables, i.e., temporal, spatial and shipment requirements variables.

variable significance and coefficient values in the likelihood function for each tour type are obtained by model estimation respectively, indicated as the format of "*variable* [tour type]" in Table 3. For example, this format "*IF_weekend* [I]" suggests that the variable of *IF_weekend* is significant for tour type I, i.e., direct tours are inclined or disinclined to be organized on weekends.

It is important to note that Pseudo-elasticities are reported for all tour types, even when a variable is statistically significant for only one tour type. In a multinomial logit framework, a change in any variable affects the choice probabilities of all alternatives through the shared probability denominator, producing cross-effects that are captured by the pseudo-elasticities. Reporting values for all tour types therefore provides a complete view of the systemwide substitution effects among alternatives. However, pseudo-elasticities associated with statistically insignificant coefficients should be interpreted cautiously, as they do not represent meaningful behavioral relationships. In addition, for variables conceptually inapplicable to specific tour types (e.g., *IF_consolidated_shipments* for direct tours), the corresponding pseudo-elasticity values have been omitted to avoid misinterpretation.

7.1. Random parameters and heterogeneity

The estimation results in Table 3 suggest that the variable *IF_weekend* is found to produce significant random parameter for direct tours with a mean and a standard deviation of 0.641 and 1.579 respectively. This suggests that for approximately 65.76 % observations, *IF_weekend* is found to have a positive effect on the likelihood of organizing direct tours, as shown in Fig. 9a. This implies that a considerable portion of the decision-makers is more inclined to opt for direct tours when the first shipment commences on the weekend. This positive effect could be due to factors such as reduced traffic congestion on weekends, allowing for faster and more efficient direct tours. Conversely, the remaining 34.24 % observations demonstrate a negative effect of *IF_weekend*. This suggests that another segment of decision-makers might have other considerations, such as the need for flexibility or the availability of resources (Yang et al., 2025b), which lead to a preference for alternative tour types.

In addition, the impact of weekend shipments on the choice of direct tours is not uniform and is influenced by the specific characteristics. For example, *IF_Manufacturing_Food* is observed to increase the mean of the random parameter for *IF_weekend* (with positive coefficient 0.554). This suggests that when shipments involve the freight sector of manufacturing-food, there is an increased tendency for individuals to favor direct tours in response to weekend shipments. Food manufacturing sector may have specific logistics considerations (e.g., time-sensitive deliveries) that make direct tours more appealing during weekends (Bosona, 2020). This is in line with the peak in demand for restaurant services in weekends. Conversely, *IF_intermed_high_demand* is found to decrease the mean of the random parameter for *IF_weekend* (with negative coefficient −1.497). This implies that when the average freight demand of the regions where intermediate locations are located is high, the positive effect of weekend shipments on the choice of direct tours becomes less prevalent. In high-demand regions, other considerations, such as the need for efficient routing to meet increased demand, might outweigh the influence of weekend shipments (Hays et al., 2002).

Another significant random parameter is associated with variable *IF_intermed_TT*, with a mean and a standard deviation of 0.792 and 1.742 respectively. We can calculate that *IF_intermed_TT* has a positive effect on

Table 2
Descriptive statistics of the explanatory variables. Note: All variables except *cargo_types* are binary dummy variables coded as 1 if the condition is met and 0 otherwise.

Explanatory Variables	Meaning	Avg.	Std.
Temporal variables			
IF_weekday	If the first shipment starts on the weekday	0.954	0.210
IF_weekend	If the first shipment starts on the weekend	0.046	0.210
IF_morning	If the first shipment starts in the morning, i.e., time period is from 04:00 to 10:59.	0.547	0.496
IF_midday	If the first shipment starts in the midday, i.e., time period is from 11:00 to 14:59.	0.131	0.382
IF_afternoon	If the first shipment starts in the afternoon, i.e., time period is from 15:00 to 20:59.	0.202	0.400
IF_night	If the first shipment starts in the night, i.e., time period is from 21:00 to 03:59.	0.120	0.238
Spatial variables			
IF_base_low_demand	If the freight demand of the region where base location is located is low, i.e., *demand* $\leq$ 197 shipments.	0.061	0.240
IF_base_medium_demand	If the freight demand of the region where base location is located is medium, i.e., 197 $<$ *demand* $\leq$ 1058 shipments.	0.147	0.354
IF_base_high_demand	If the freight demand of the region where base location is located is high, i.e., *demand* $>$ 1058 shipments.	0.792	0.406
IF_intermed_low_demand	If the average freight demand of the regions where the intermediate locations are located is low, i.e., *demand* $\leq$ 197 shipments.	0.388	0.487
IF_intermed_medium_demand	If the average freight demand of the regions where the intermediate locations are located is medium, i.e., 197 $<$ *demand* $\leq$ 1058 shipments.	0.267	0.443
IF_intermed_high_demand	If the average freight demand of the regions where the intermediate locations are located is high, i.e., *demand* $>$ 1058 shipments.	0.344	0.475
IF_base_low_congestion	If the congestion level of the region where base location is located is low, i.e., *delay time* $\leq$ 13.95 s.	0.259	0.438
IF_base_medium_congestion	If the congestion level of the region where base location is located is medium, i.e., 13.95 s $<$ *delay time* $\leq$ 35.739 s.	0.551	0.497
IF_base_high_congestion	If the congestion level of the region where base location is located is high, i.e., *delay time* $>$ 35.739 s.	0.190	0.392
IF_intermed_low_congestion	If the average congestion level of the regions where the intermediate locations are located is low, i.e., *delay time* $\leq$ 13.95 s.	0.270	0.444
IF_intermed_medium_congestion	If the average congestion level of the regions where the intermediate locations are located is medium, i.e., 13.95 s $<$ *delay time* $\leq$ 35.739 s.	0.505	0.500
IF_intermed_high_congestion	If the average congestion level of the regions where the intermediate locations are located is high, i.e., *delay time* $>$ 35.739 s.	0.225	0.417
IF_base_low_distance	If the average distance from base location to all intermediate locations is low, i.e., *distance* $\leq$ 32 km.	0.565	0.496
IF_base_medium_distance	If the average distance from base location to all intermediate locations is medium, i.e., 32 km $<$ *distance* $\leq$ 72 km.	0.252	0.434
IF_base_high_distance	If the average distance from base location to all intermediate locations is high, i.e., *distance* $>$ 72 km.	0.183	0.386
IF_intermed_low_distance	If the average distance between intermediate locations is low, i.e., *distance* $\leq$ 32 km.	0.806	0.395
IF_intermed_medium_distance	If the average distance between intermediate locations is medium, i.e., 32 km $<$ *distance* $\leq$ 72 km.	0.127	0.333
IF_intermed_high_distance	If the average distance between intermediate locations is high, i.e., *distance* $>$ 72 km.	0.067	0.250
Shipment requirements variables			
IF_base_TT	If the base location is the freight agent of TT.	0.185	0.389
IF_base_DC	If the base location is the freight agent of DC.	0.292	0.455
IF_base_PC	If the base location is the freight agent of P/C.	0.523	0.500
IF_intermed_TT	If there is a TT among intermediate locations.	0.184	0.388
IF_intermed_DC	If there is a DC among intermediate locations.	0.513	0.500
IF_intermed_PC	If there is a P/C among intermediate locations.	0.741	0.438
cargo_types	Number of types of cargo transported.	1.736	1.089
IF_consecutive_shipments	If there are consecutive shipments.	0.512	0.500
IF_consolidated_shipments	If there are consolidated shipments.	0.808	0.394
IF_Manufacturing_NonFood	If the shipments involve the freight sector of Manufacturing-NonFood.	0.480	0.500
IF_Manufacturing_Food	If the shipments involve the freight sector of Manufacturing-Food.	0.231	0.422
IF_WholeSale	If the shipments involve the freight sector of WholeSale.	0.629	0.483
IF_Agriculture	If the shipments involve the freight sector of Agriculture.	0.105	0.306
IF_Horeca	If the shipments involve the freight sector of Horeca.	0.072	0.259
IF_Storage_and_Transport	If the shipments involve the freight sector of Storage & Transport.	0.238	0.426
IF_Auto_Heavy_Machines	If the shipments involve the freight sector of Auto Heavy Machines.	0.159	0.365
IF_Construction	If the shipments involve the freight sector of Construction.	0.126	0.331
IF_Retail	If the shipments involve the freight sector of Retail.	0.163	0.369
IF_Raw_Materials	If the shipments involve the freight sector of Raw Materials.	0.007	0.083
IF_Utility	If the shipments involve the freight sector of Utility.	0.002	0.047
IF_Chemicals	If the shipments involve the freight sector of Chemicals.	0.022	0.148
IF_Waste_Management	If the shipments involve the freight sector of Waste Management.	0.012	0.109
IF_Minerals	If the shipments involve the freight sector of Minerals.	0.001	0.028

Table 3
Estimation results for random parameters logit model with heterogeneity in means and variances.

Variables	Coeff.	t-stat	Pseudo-elasticities		
			direct tour	sequential tour	complex tour
Constant [I]	2.425***	7.40			
Temporal characteristics					
IF_weekend [I] (random parameter)	0.641**	2.45	**0.0037**	−0.2509	−0.2806
IF_midday [II]	−0.793**	−2.40	0.0117	**−0.0403**	0.0353
Spatial characteristics					
IF_intermed_low_demand [I]	1.119**	2.38	**0.0819**	−0.1266	−0.1305
IF_intermed_low_demand [III]	−0.432***	−3.99	0.0096	0.0173	**−0.0693**
IF_intermed_high_congestion [I]	−0.620***	−5.92	**−0.0263**	0.0887	0.0469
IF_base_low_distance [I]	0.867***	7.26	**0.2948**	−0.0955	−0.183
IF_base_high_distance [III]	0.212*	1.76	−0.0061	−0.0091	**0.0173**
Shipment requirements characteristics					
IF_intermed_DC [II]	1.383***	6.02	−0.1919	**0.0786**	−0.1978
IF_intermed_TT [III] (random parameter)	0.792***	8.24	−0.0393	−0.0646	**0.0785**
IF_consecutive_shipments [I]	−0.667***	−4.82	**−0.1411**	0.0983	0.1018
IF_consolidated_shipments [III]	0.963***	2.91	N/A	−0.0053	**0.0061**
IF_Manufacturing_Food [I]	1.437***	6.63	**0.3122**	−0.1695	−0.1762
IF_WholeSale [I]	0.547***	5.26	**0.2445**	−0.0840	−0.0117
IF_Auto_Heavy_Machines [II]	−0.751***	−4.15	0.0510	**−0.0350**	0.0364
IF_Manufacturing_NonFood [II]	0.311***	3.30	−0.0374	**0.0839**	−0.0618
IF_Storage_and_Transport [III]	1.195***	11.36	−0.0786	−0.0355	**0.0431**
Heterogeneity in the mean of the random parameters					
IF_weekend [I]: *IF_Manufacturing_Food*	0.554***	2.79			
IF_weekend [I]: *IF_intermed_high_demand*	−1.497***	−3.49			
IF_intermed_TT [III]: *IF_base_high_distance*	2.063***	2.94			
IF_intermed_TT [III]: *Agriculture*	1.087**	2.01			
IF_intermed_TT [III]: *IF_consecutive_shipments*	0.344**	2.43			
Standard deviation of parameter estimate (normally distributed)					
IF_weekend [I]	1.579***	3.12			
IF_intermed_TT [III]	1.742**	2.28			
Goodness-of-fit measures					
Number of observations	5000				
Number of parameters	49				
$LL(0)$- Log-likelihood at zero	−5148.265				
$LL(\boldsymbol{\beta})$- Log-likelihood at convergence	−3317.552				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.3556				
R-Squared	0.214				
Adjusted R-Squared	0.210				
AIC (Akaike Information Criterion)	8733.1				

Note: variables not shown here are insignificant. Parameters defined for [I] direct tour, [II] sequential tour, [III] complex tour. *p < 0.1, **p < 0.05 and ***p < 0.01 for statistical significance. Pseudo-elasticities represent the percentage change in the probability of each tour type for a one-unit change in the explanatory variable. Variables significant for one tour type affect probabilities of all tour types through the multinomial logit structure. Bold pseudo-elasticity values indicate direct effects where the variable is statistically significant for that tour type, while non-bold values represent indirect cross-effects through probability normalization.

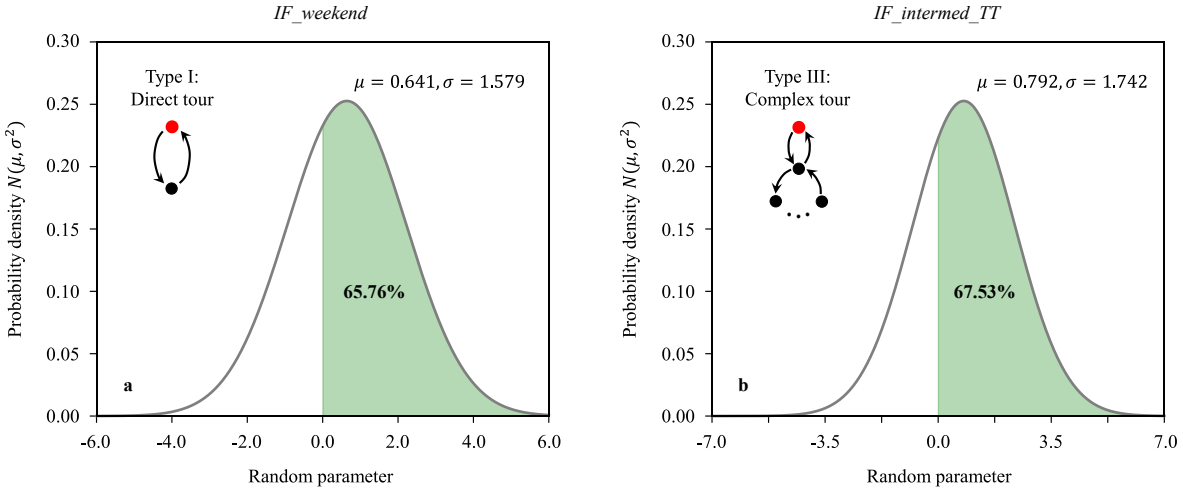


Fig. 9. Distributions of random parameters estimated in the RPLH model. **a** Random parameter associated with variable *IF_weekend* for direct tours. **b** Random parameter associated with variable *IF_intermed_TT* for complex tours. μ and σ indicate the estimated mean and standard deviation for the normal distribution $N(\mu,\sigma^2)$, from which random parameters are assumed to be drawn. Green area indicates that the parameter is greater than 0, i.e., the variable positively influences the opting of specific tour type. The number marked in the green area indicates the ratio of observations that the corresponding variable has a positive effect. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the likelihood of organizing complex tours (Table 3) for 67.53 % of the observations, while has a negative effect on the remaining observations, as shown in Fig. 9b. The individual heterogeneity and preferences observed in response to the *IF_intermed_TT* variable underscores the multifaceted nature of decision-making in organizing complex tours. For the majority of operators (67.53 %), the presence of a transshipment terminal among intermediate locations encourages a preference for complex tours. These decision-makers prioritize the operational advantages that transshipment terminals offer, such as efficient cargo consolidation, flexible routing options, and the ability to coordinate multiple pickups and deliveries within a single tour (Montecinos et al., 2021). The infrastructure and handling capabilities of transshipment terminals make them well-suited for managing the logistical complexity inherent in multi-stop tours. However, for the remaining operators (32.47 %), other operational priorities dominate their decision-making. These may include minimizing total travel time, reducing cargo handling frequency to ensure product integrity, avoiding terminal fees or delays, or maintaining simpler operational procedures that require less coordination. For these decision-makers, even when transshipment terminals are available, the potential benefits do not outweigh the costs or risks associated with more complex tour structures. This divergence in preferences demonstrates that tour organization decisions involve balancing multiple competing objectives—efficiency, cost, time, reliability, and simplicity—and that the relative importance of these objectives varies substantially across different operational contexts and decision-maker priorities.

We can also observe that variables *IF_base_high_distance* (with coefficient of 2.063), *IF_Agriculture* (with coefficient of 1.087) and *IF_consecutive_shipments* (with coefficient of 0.344) are found to increase the mean of the random parameter associated with *IF_intermed_TT*. This suggests that in scenarios where the logistics entail covering longer distances between the base location and intermediates, the presence of a transshipment terminal among those intermediates becomes more appealing for organizing complex tours, helping mitigate the challenges associated with long-distance hauls (Archetti et al., 2022). Moreover, agriculture-related shipments may have unique requirements that align well with the utilization of transshipment terminals, potentially for storage, sorting, or handling purposes. Also, consecutive shipments may require careful coordination and consolidation, and the presence of a transshipment terminal can facilitate this process, leading to a preference for complex tours in such scenarios.

7.2. Temporal characteristics

In the above, we have uncovered the heterogenous effects of two explanatory variables on the organization of truck tours by analyzing the random parameters and the heterogeneity in their means. There are many other variables that do not produce significant random parameters, but still provide insights into the characteristics of three distinct truck tours. For temporal characteristics, the *IF_midday* variable has negative coefficients for sequential tours (type II), with t-statistics of −2.40. This indicates that when the first shipment starts in the midday period (from 11:00 to 14:59), there is a significant preference against organizing sequential truck tours. There may be practical or logistical challenges associated with midday start times that make them less favorable. These challenges could include factors such as increased traffic congestion, limited availability of resources, or disruptions in scheduling during the midday hours (Laranjeiro et al., 2019). The results highlight the importance of temporal considerations in the decision-making process for different truck tour types.

7.3. Spatial characteristics

Next, we analyze how various spatial factors influence the organization of truck tours. In the case of direct tours, the variable *IF_intermed_low_demand* has a positive coefficient (1.119), indicating that when the average freight demand of regions with intermediate locations is low, there is a higher likelihood of the tour being categorized as a direct tour. This suggests that lower demand in these regions is associated with simpler and more streamlined logistical arrangements. In contrast, the variables *IF_intermed_low_demand* exhibits a negative coefficient (−0.432) for complex tours. This indicates that when there is a substantial demand in the areas where intermediate stops are made, it becomes more efficient or profitable to conduct sequential or complex tours, which may involve picking up and delivering goods at multiple locations. Moreover, the variable *IF_intermed_high_congestion* has a negative coefficient (−0.620) for direct tours, implying that higher congestion levels in intermediate regions tend to discourage the selection of direct tours, possibly due to the logistical challenges posed by congestion (Ahmed et al., 2019). Direct tours typically involve transporting goods with minimal stops, aiming for efficiency and speed.

Lastly, the coefficients for the distance-related variables indicate that shorter distances between the base location and intermediate stops significantly increase the likelihood of direct tour organization (variable *IF_base_low_distance* has a positive coefficient 0.867). When intermediate stops are closer to the base, it becomes more efficient and cost-effective to conduct direct tours. Shorter distances reduce operational expenses and ensure quicker delivery times, which can be critical to meet customer expectations (Pang et al., 2025). Furthermore, the variables *IF_base_high_distance* has a positive coefficient of 0.212 for complex tours. This implies that complex tours involve a combination of long-distance travel from the base to the various intermediate locations, coupled with the efficient clustering of these intermediate locations in terms of proximity.

7.4. Shipment requirements characteristics

The estimation results can also help understand how truck tours are designed to meet the specific shipment requirements of different freight agents and sectors.

In the first set of variables related to freight agents involved in shipments, we can observe that the presence of DC (distribution center) among intermediate locations significantly promotes the choice of sequential tours, as indicated by the positive coefficient (1.383) of *IF_intermed_DC*. This implies that logistics planners may prefer to visit distribution centers when organizing sequential tours, possibly to optimize loading and unloading operations (Comi et al., 2018).

The second set of variables related to shipment structure reveals that consecutive shipments are less likely to occur in direct tours (*IF_consecutive_shipments* with negative coefficient −0.667). As in direct tours there is often not an exact mirrored shipment available for the return trip. Additionally, complex tours are more likely to involve consolidated shipments (*IF_consolidated_shipments* with positive coefficient 0.963), which suggests that grouping multiple shipments together can be a practical strategy for this tour type, potentially reducing overall transportation costs.

In the third set of variables regarding the freight sectors served in shipments, manufacturing-food and wholesale sectors positively impact the choice of direct tours with coefficients of 1.437 and 0.547, respectively, which is also indicated in the high pseudo-elasticity for direct tours. This suggests that these sectors are more likely to opt for direct tours, possibly to ensure timely delivery of perishable goods or bulk products (Morganti and Gonzalez-Feliu, 2015). For sequential tours, *IF_Auto_Heavy_Machines* has a negative coefficient (−0.751) and *IF_Manufacturing_NonFood* has a positive coefficient (0.311). This indicate that sequential tours are less likely for heavy machinery shipments but more likely for non-food manufacturing shipments. Heavy machinery shipments might require specialized handling, take up more space in a truck, or have different scheduling requirements to be included in a sequential truck tour. Non-food manufacturing shipments might be more standardized, have predictable schedules, or be compatible with other shipments in a way that makes sequential routing more efficient. Lastly,

for complex tours, positive coefficient of storage & transport (1.195) sector indicate that trucks prefer to visit specific intermediate locations multiple times during their tours, possibly due to the nature of cargo or logistical considerations of these sectors (Wu and Haasis, 2018).

8. Discussion

This research makes a critical contribution by moving beyond descriptive tour pattern analysis to model the complex, heterogeneous decision-making processes underlying tour organization. By leveraging a large-scale, shipment-based dataset and an advanced random parameters logit model with heterogeneity in means and variances (RPLH), we uncover not only what tour patterns exist, but why specific patterns are chosen under different conditions. This behavioral understanding provides substantial practical and policy implications for multiple stakeholders.

8.1. Strategic implications for logistics operators

While logistics companies possess detailed knowledge of their own operations, their understanding is necessarily constrained by their specific client portfolios, served sectors, and operational experience. Our study provides two essential insights unavailable from internal company data.

First, our findings establish industry-wide benchmarks that enable operators to evaluate and refine their strategies. For instance, an operator primarily serving the wholesale sector might predominantly organize sequential tours. However, our model results reveal that direct tours are strongly favored for wholesale shipments under specific conditions (e.g., weekend operations, low-congestion destinations, coefficient 0.547). This evidence can motivate operators to explore service differentiation, such as offering direct weekend delivery service, to capture efficiency gains that may not be apparent from their own limited operational history.

Second, by modeling heterogeneous effects, we quantify the fundamental strategic trade-offs driving tour organization choices. For instance, the random parameter for *IF_intermed_TT* exemplifies this contribution. It reveals a substantial divergence in preferences: 67 % of observations favor utilizing transshipment terminals for network efficiency and consolidation benefits, while 33 % prioritize service speed and operational simplicity by avoiding terminals. Operators can leverage this insight to develop explicit, evidence-based guidelines for when each strategy is appropriate, moving beyond informal planner judgment (Li et al., 2021; Ye et al., 2020; Zhao et al., 2020). This system-level perspective reveals the range of effective logistics strategies employed across the freight sector, enabling companies to identify and adopt approaches beyond their established practices (Hasan et al., 2020; Liu et al., 2023).

8.2. Targeted interventions for policymakers

The primary policy contribution of this research is providing an analytical foundation for context-specific interventions rather than uniform regulations. Our model demonstrates that tour organization decisions are highly context-dependent, and effective policies must account for this heterogeneity.

Consider the objective of promoting off-peak deliveries to reduce urban congestion (Beheshtian et al., 2020; Campbell et al., 2018). Blanket incentive programs may prove ineffective because many sectors face rigid constraints from receiver business hours and operational requirements. Our model can identify sectors with inherent flexibility. We find that the food manufacturing sector demonstrates increased preference for direct tours on weekends (coefficient 0.554), indicating temporal flexibility in these supply chains. Policymakers can use this evidence to design targeted incentive programs specifically for food manufacturers and their primary receivers (e.g., supermarkets, restaurants) to shift deliveries to early morning or weekend time windows, substantially improving program effectiveness compared to undifferentiated approaches.

Similarly, for infrastructure planning (Machado et al., 2023), our results provide specific spatial guidance. The finding that complex tours combine long base-to-intermediate distances (coefficient 2.063) with spatially clustered intermediate stops reveals a distinct spatial pattern. Urban planners can identify peripheral zones that function as critical staging areas for multi-stop urban delivery tours. These locations represent high-priority investment opportunities for supporting infrastructure such as dedicated loading zones, freight-priority lanes, or urban consolidation centers, ensuring efficient allocation of public infrastructure funding.

Our findings emphasize that the freight system comprises interdependent stakeholders, and interventions in one area generate consequences throughout the system. Effective policies and operational changes must anticipate these interdependencies, particularly impacts on receivers. For instance, if policies successfully shift food deliveries to off-peak periods, receivers, including supermarkets and restaurants, must adapt by staffing facilities to accept shipments outside traditional business hours, potentially increasing labor costs and operational complexity. The value of our research lies in providing the empirical foundation for multi-stakeholder coordination. By identifying sectors with inherent flexibility and quantifying the factors influencing their decisions, our model establishes the foundation for collaborative, evidence-based policymaking that balances stakeholder needs and constraints, supporting more efficient and sustainable urban freight systems.

9. Conclusion

In the paper, we have conducted a comprehensive analysis of more than 1000 different tour patterns of freight trucks in the Netherlands, based on large-scale carrier and shipment data. We classified these patterns into three types: direct tours, sequential tours, and complex tours, reflecting diverse logistical strategies. We further examined the factors influencing the organization of these tours, considering temporal, spatial, and shipment requirements characteristics. Our findings demonstrate the multifaceted nature of truck tour patterns and highlight the importance of tailored logistics solutions. Furthermore, we introduced a novel approach using random parameters logit models with heterogeneity in means and variances, providing a more nuanced understanding of decision-making processes. Notably, we identified that specific variables, such as weekend shipments, transshipment terminals, and freight sector considerations, significantly impact tour choices. Overall, our research deepens our understanding of the multifaceted nature of truck tour patterns, potentially offering practical implications for logistics management, urban planning, and policy development.

While this study provides valuable insights, it is important to acknowledge its limitations. First, the analysis is based on data from 2015. The freight and logistics landscape has since evolved, influenced by the rapid growth of e-commerce, the COVID-19 pandemic, and new sustainability regulations. Therefore, while the fundamental behaviors modeled are likely still relevant, the specific magnitudes of effects may have changed. Second, the dataset is company-reported shipment data, not GPS tracking data. While this provides unparalleled detail on cargo characteristics, it lacks the granular spatial and temporal information of vehicle trajectories. Our model, therefore, predicts the choice of tour structure (e.g., direct vs. complex) but cannot analyze the route choice between stops. Third, the findings are specific to the Dutch context, which is characterized by a dense, polycentric urban structure. In this environment, the boundaries between urban and regional areas are often blurred, making a simple binary classification of tour patterns difficult. Consequently, our analysis relies on continuous distance metrics rather than categorical urban/regional variables to capture the operational scale. The generalizability of these results to countries with

clearer urban-rural divides should be approached with caution. Finally, like any statistical model, our analysis is constrained by the variables available in the dataset. Other unobserved factors, such as specific contractual delivery windows, driver work-hour rules, or the use of real-time traffic information, could also influence tour organization but were not captured in this study.

These limitations also highlight meaningful avenues for future improvements. First, future studies can focus on exploring the integration of more recent datasets and real-time data from advanced technologies like GPS tracking (Yang et al., 2022b) and IoT devices (Aguirre-Jofré et al., 2021). Fusing rich shipment data, as used here, with granular trajectory data would allow for a joint analysis of tour structure and route choice, enhancing the accuracy and applicability of the analysis for more dynamic and responsive logistics strategies. Future work could also attempt to integrate advanced geofencing techniques to explicitly categorize operational zones (urban vs. regional) to further investigate the heterogeneity of tour patterns across different spatial scales.

Second, an emerging research direction involves exploring the integration of passenger and freight services within urban transportation systems. Recent literature has highlighted the potential of shared mobility solutions, such as utilizing passenger vehicles or public transit for freight delivery during off-peak hours (de Oliveira et al., 2017; Mourad et al., 2019). Our methodological framework for analyzing heterogeneous tour patterns could be extended to evaluate how passenger-freight integration affects route organization, delivery efficiency, and urban congestion. Such integration presents both opportunities (e.g., improved vehicle utilization, reduced empty trips) and challenges (e.g., coordination complexity, service quality trade-offs) that warrant systematic investigation.

Third, future research should conduct comprehensive impact assessments quantifying the social benefits of optimized freight tour organization. This includes evaluating reductions in traffic congestion, air pollution, and greenhouse gas emissions resulting from targeted policy interventions (Zhi et al., 2024) informed by our behavioral model. Understanding these broader societal impacts would provide policymakers with evidence-based cost-benefit analyses to justify infrastructure investments and regulatory reforms, ultimately supporting more sustainable and efficient urban freight systems.

CRediT authorship contribution statement

Yitao Yang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Ali Nadi:** Writing – review & editing, Writing – original draft, Validation, Formal analysis, Data curation. **Dongdong Song:** Writing – review & editing, Writing – original draft, Software, Methodology. **Merve Seher Cebeci:** Writing – review & editing, Writing – original draft, Visualization, Resources, Formal analysis. **Bin Jia:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition. **Michiel de Bok:** Writing – review & editing, Writing – original draft, Supervision, Project administration. **Lóránt A. Tavasszy:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration.

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Data availability

The authors do not have permission to share data.

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