Urban freight mobility modes recognition classification and inclusive freight policy exploration based on truck trajectory data: A case study of Shanghai, China

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Abstract
In high-density cities like Shanghai, freight trucks are essential but face significant constraints and high costs. This study addresses the shortfalls of current "one-size-fits-all" freight policies. Using extensive GPS data from heavy trucks and a two-step clustering method, the research identifies typical activity patterns from a micro-perspective. It classifies truck activities into two main categories and five sub-categories, revealing significant differences in travel distance, hub stops, and journey types (intra-city vs. inter-city). Based on these findings, the study proposes targeted management suggestions, such as more detailed requirements for short-distance trucks and flexible traffic restrictions informed by big data, paving the way for innovative, localized urban freight systems.

Keywords: Freight mobility modes, Inclusive policies, Sustainable mobility systems, Truck trajectory data, Shanghai

1. Introduction

1.1. Background and Significance

The intricate web of freight transportation is indispensable to the daily lives of households and the seamless operations of businesses, profoundly influencing urban development and prosperity. Within the dense fabric of high-density urban areas, freight trucks serve as the undisputed backbone of goods movement. However, their critical role is often juxtaposed with significant operational constraints and substantial costs (Li, 2020). Understanding the nuanced behaviour of freight trucks is not merely an academic exercise; it is foundational for enhancing the efficiency of freight transport, optimising supply and demand forecasting, and refining urban governance strategies.

Historically, the analysis of freight activity has often relied on aggregated data or macroscopic models, which can obscure the underlying complexities of individual truck movements. This 'one-size-fits-all' approach to freight policy, while administratively convenient, frequently overlooks the diverse operational requirements and characteristics of various freight activities. This oversight can lead to inefficiencies, increased costs for logistics operators, and exacerbated urban challenges such as traffic congestion, air pollution, and noise (Liu and Zhang, 2023).

The necessity of delving deeper into urban freight truck activity is multifaceted. Firstly, from an economic perspective, gaining a profound understanding of these behaviours can significantly contribute to cost reduction and efficiency gains within the freight transport sector, thereby fostering economic growth. Secondly, from an urban planning and management viewpoint, a detailed analysis of truck activity patterns is an imperative for the precise refinement of urban traffic governance and the substantial improvement of road network operational efficiency. Traditional approaches to urban freight management often lack the granularity required to implement effective, tailored policies that acknowledge the varied functions and impacts of different truck operations.

The feasibility of conducting such micro-level research has dramatically improved in recent years. The proliferation of high-frequency truck trajectory data, primarily derived from Global Positioning System (GPS) devices, has opened unprecedented avenues for detailed observation and analysis. This wealth of data makes it possible to investigate the microscopic patterns of truck activity, uncover underlying behavioural regularities, and construct more sophisticated models of freight movement (Ma et al., 2016; You and Ritchie, 2018). This study leverages these advancements to provide a comprehensive analysis of urban freight mobility in Shanghai, China.

1.2. Research Content

This study aims to address the aforementioned gaps by undertaking a detailed examination of freight truck activity patterns, supported by extensive high-frequency trajectory data. The research encompasses several key areas:

- **Characterisation of Truck Travel Characteristics:** Utilising high-frequency truck trajectory data, the study first focuses on identifying stop points and performing path map matching. This process extracts fundamental travel information, which is then used to characterise various aspects of truck travel, including trip duration and frequency, spatial distance and range, and the utilisation of infrastructure.
- **Inference of Truck Activity Purpose:** By integrating diverse data sources such as land use, enterprise registration information, and Points of Interest (POI) data, the research moves beyond a mere empirical understanding of individual truck trajectories. It explores methodologies to infer the specific purposes behind observed truck activities, providing crucial insights into the 'why' of their movements.
- **Categorisation of Truck Activity Modes:** Drawing upon the insights gleaned from the characterisation of truck travel characteristics and the inference of activity purposes, the study aims to summarise typical truck activity modes. This involves exploring classification methods to identify distinct patterns of freight movement.
- **Management Recommendations for Different Truck Activity Types:** Based on the identified and categorised truck activity types, the research proposes management recommendations. These suggestions are developed in consideration of existing urban freight management policies and are designed to be more congruent with industry needs and the inherent patterns of truck activity. The ultimate goal is to formulate more inclusive and effective freight policies that cater to the diverse operational demands of urban logistics.

2. Literature Review

Understanding freight truck movement patterns is a multidisciplinary challenge that draws insights from urban planning, logistics, transportation engineering, and data science. This section reviews existing literature, highlighting key methodologies and findings pertinent to this study.

2.1. Stop Point Identification

The identification of "stop points" or "stay points" from raw GPS trajectory data is a crucial preliminary step for understanding vehicle behaviour. A stop point signifies a period when a vehicle remains stationary or moves within a very limited area, often indicating an activity such as loading, unloading, parking, or waiting. Various methods have been proposed for stop point identification, typically involving thresholds for speed, time, and spatial proximity.

Early approaches often relied on simple speed thresholds, deeming any point below a certain speed as part of a stop (e.g., Wang et al., 2012). However, this can be problematic in congested urban environments where slow movement does not necessarily equate to a stop. More sophisticated methods incorporate time thresholds, defining a stop as a period where the vehicle remains within a predefined spatial radius for a minimum duration (e.g., Li, 2020). For instance, Li (2020) utilised a method that clusters GPS points within a certain radius and time window to identify stop points, a common practice in freight research.

Recent advancements in stop point detection involve more complex algorithms, including density-based spatial clustering of applications with noise (DBSCAN) or grid-based methods, which are more robust to GPS signal fluctuations and varying speeds. Ji et al. (2019) proposed a parallel algorithm that combines stay point features and moving features to detect traffic patterns, showcasing the evolution towards more integrated approaches. The accuracy of stop point identification directly impacts the subsequent analysis of activity chains and trip purposes.

2.2. Freight Trip Chaining Analysis

Freight trip chaining, or the sequence of stops and movements that constitute a complete vehicle tour, offers a holistic view of freight operations. Unlike passenger trips, freight tours often involve multiple stops for pick-ups and deliveries, making the concept of "trip chaining" particularly relevant. Analysing these chains helps in understanding the operational logic, efficiency, and spatial distribution of freight activities.

Ma et al. (2016) explored freight trip-chaining behaviour using a spatial data-mining approach with GPS data, revealing common patterns and influencing factors. Their work underscored the importance of geographical context in understanding trip structures. Similarly, You and Ritchie (2018) developed a GPS data processing framework specifically for the analysis of drayage truck tours, highlighting the unique characteristics of port-related freight movements.

The duration and sequence of stops within a trip chain are critical indicators of efficiency and potential bottlenecks. Duan et al. (2020) further advanced this area by comprehending and analysing multiday trip-chaining patterns of freight vehicles using a multiscale method with prolonged trajectory data, demonstrating the complexity and continuity of freight operations over longer periods. Their research emphasized that freight vehicles often exhibit complex multi-day activity patterns, not just simple round trips. Liu and Zhang (2023) focused on identifying urban freight stay behaviour based on truck GPS data, providing a model that can pinpoint where and for how long trucks pause, which is crucial for infrastructure planning.

2.3. Freight Activity Purpose Inference
Inferring the purpose of freight activities is perhaps the most challenging aspect, as GPS data alone provides location and movement, not intent. This typically requires integrating external data sources, such as land use, Points of Interest (POI), and business registration data.

For instance, a truck stopping at a logistics park or warehouse is likely involved in loading/unloading, while a stop at a retail area might indicate delivery to a store. Chen et al. (2022) analysed the spatiotemporal differences and influencing factors of heavy freight vehicle travel, implicitly touching upon the varied purposes behind these movements. The integration of land use data allows researchers to contextualise stops, inferring purposes based on the type of activity typically conducted at that location. For example, stops in industrial zones often relate to manufacturing or warehousing, while stops in commercial areas are usually for retail delivery.

Some studies have employed machine learning techniques to classify activity purposes based on a combination of GPS features (e.g., duration of stay, frequency of visits, average speed) and external data. However, the accuracy of such inference heavily relies on the quality and granularity of the supplementary data. The challenge lies in developing robust methodologies that can accurately distinguish between, for example, a delivery stop, a maintenance stop, or a driver rest stop.

2.4. Freight Activity Mode Classification
Building upon trip chaining and purpose inference, the next logical step is to classify recurring freight activity patterns into distinct "modes" or "typologies." This classification helps in understanding the heterogeneity of freight operations and developing targeted policies.
Common classification criteria include:

- **Journey Type:** Intra-city vs. inter-city, reflecting different operational scales and regulatory environments.
- **Vehicle Type:** Heavy-duty vs. light-duty trucks, each with different capacities, speeds, and road access restrictions.
- **Cargo Type:** While difficult to infer directly from GPS, this is a key differentiator in freight logistics.
- **Operational Pattern:** E.g., hub-and-spoke operations, direct deliveries, multi-stop routes, return trips, or maintenance trips.

Research often uses clustering algorithms (e.g., K-means, hierarchical clustering, or two-step clustering) to group similar trip chains or activity sequences. The effectiveness of these classifications depends on the features used for clustering, which can include trip distance, duration, number of stops, stop duration distribution, and inferred activity purposes. The aim is to identify distinct operational profiles that can be used for policy differentiation.

2.5. Inclusive Freight Policy Development
Traditional urban freight policies often adopt a blanket approach, applying the same restrictions or incentives to all freight vehicles regardless of their specific operational needs. This can lead to inefficiencies, increased costs for businesses, and unintended negative consequences. The reviewed literature strongly suggests a move towards more "inclusive" or "differentiated" freight policies that acknowledge the diversity of freight activities.

Such policies could include:

- **Time-window restrictions:** Differentiated by vehicle type or purpose.
- **Access restrictions:** Based on emission standards, vehicle size, or specific routes.
- **Loading/Unloading Zones:** Strategically located and managed to minimise disruption.
- **Pricing mechanisms:** Such as congestion charges or differentiated tolls.

The core idea is to tailor regulations to the specific characteristics of different freight activity modes. For instance, short-distance, intra-city deliveries might require different policy interventions than long-haul inter-city movements. This requires a granular understanding of freight behaviour, which is precisely what the preceding research areas aim to provide.

This study aims to bridge the gap between microscopic behavioural analysis and macroscopic policy formulation, offering data-driven insights for more effective and inclusive urban freight management in Shanghai.

3. Data and Methodology
This section details the data sources utilised and the methodologies employed for stop point identification, truck trip generation, and activity mode clustering.

3.1. Data Sources
The primary data source for this study is high-frequency GPS trajectory data from a large fleet of heavy freight trucks operating in Shanghai. This dataset provides a rich, granular record of truck movements over an extended period. Each GPS record typically includes:

- **Vehicle ID:** Unique identifier for each truck.
- **Timestamp:** Date and time of the GPS recording.
- **Latitude and Longitude:** Geographical coordinates of the truck's location.
- **Speed:** Instantaneous speed of the truck.
- **Direction:** Bearing of the truck's movement.

The data covers a significant number of heavy trucks, ensuring a representative sample of freight activity within and around Shanghai. The high frequency of data points (e.g., every few seconds or minutes) allows for precise identification of movement patterns and stationary periods.

In addition to GPS data, the study incorporates supplementary data for activity purpose inference:
- **Land Use Data:** Provides information on the predominant activities in different urban zones (e.g., industrial, commercial, residential). This helps contextualise truck stops.
- **Points of Interest (POI) Data:** Offers specific information about businesses, facilities, and infrastructure (e.g., logistics parks, warehouses, retail centres, wholesale markets). POI data is crucial for inferring the specific nature of activities at stop points.
- **Enterprise Registration Data (where available):** Can provide insights into the type of business operating at a specific location, further aiding in purpose inference.

3.2. Stop Point Identification
Accurate identification of stop points is fundamental for segmenting continuous GPS trajectories into discrete trips and activities. The methodology for stop point identification in this study combines spatial and temporal thresholds to distinguish genuine stops from brief pauses or slow movements due to traffic.

The process involves:
a) **Initial Filtering:** Raw GPS data is first cleaned to remove outliers or erroneous readings (e.g., sudden jumps in location or unrealistic speeds).
b) **Candidate Stop Point Detection:** For each truck, consecutive GPS points are examined. If a sequence of points exhibits a speed below a predefined threshold (e.g., 5 km/h) for a continuous duration exceeding a minimum time threshold (e.g., 5 minutes), these points are flagged as a potential stop.
c) **Spatial Clustering:** Candidate stop points are then clustered spatially. If multiple GPS points from the

same truck within a short time window fall within a small geographical radius (e.g., 50 meters), they are grouped into a single stop point. The centroid of these clustered points is designated as the stop location.

d) **Stop Duration Calculation:** The duration of a stop is calculated from the timestamp of the first point to the last point within the identified stop cluster.

e) **Trip Segmentation:** Once stop points are identified, the continuous trajectory is segmented into individual "trips" (movements between two stop points) and "stops." A typical trip chain would look like: Stop A – Trip 1 – Stop B – Trip 2 – Stop C, and so on.

The selection of appropriate speed, time, and spatial thresholds is critical and often determined through empirical analysis of the data and domain knowledge to best represent actual truck activities.

3.3. Truck Trip Generation

Following stop point identification, individual truck trips are generated. A "trip" is defined as the movement segment between two consecutive stop points. For each generated trip, key attributes are extracted:

- **Origin Stop ID and Destination Stop ID:** Linking trips to their respective start and end locations.
- **Trip Start Time and End Time:** Derived from the timestamps of the origin and destination stop points.
- **Trip Duration:** Calculated as the difference between end and start times.
- **Trip Distance:** Calculated by summing the distances between consecutive GPS points along the trajectory, or using map-matched distances.
- **Average Speed:** Total distance divided by total duration.
- **Number of GPS Points:** Indicating the data density for the trip.

3.4. Path Map Matching

To enhance the accuracy of trip distances and ensure that trajectories align with the actual road network, a path map-matching algorithm is applied. This process maps the raw GPS points onto the most probable roads on a digital map. Map matching helps:

- **Correct GPS Errors:** Reducing the impact of signal drift or inaccuracies.
- **Obtain Realistic Distances:** Calculating distances along the actual road network, which is more accurate than straight-line distances or distances derived from raw GPS points in complex urban environments.
- **Identify Road Segments Used:** Providing insights into routing patterns and network utilisation.

The map-matching process typically involves algorithms that consider the proximity of GPS points to road segments, the topological connectivity of the road network, and the sequence of GPS points.

3.5. Inference of Truck Activity Purpose

Inferring the purpose of a truck's activity at a stop point is a complex task. This study employs a rule-based approach, combining geographical context from land use data and specific facility information from POI data. The methodology involves:

a) **Geocoding Stop Points:** Each identified stop point is geocoded to obtain its precise location.

b) **Overlay with Land Use Data:** The stop point location is overlaid with urban land use maps. This provides a general categorisation of the area (e.g., industrial zone, commercial area, residential area, logistics park).

c) **Proximity Analysis with POI Data:** A buffer zone (e.g., 100-200 meters) is created around each stop point. All POIs within this buffer are identified.

d) **Rule-Based Inference:** A set of heuristic rules is applied to infer the activity purpose. Examples of rules include:

o If a stop is in an industrial zone and near a warehouse or factory POI, the purpose is likely "Loading/ Unloading - Industrial."
o If a stop is in a commercial area and near a retail store or supermarket POI, the purpose is likely "Delivery - Commercial."
o If a stop is near a logistics park or distribution centre POI, it's likely "Transshipment/Distribution."
o If a stop is prolonged and near a residential area, it might be "Driver Rest" or "Home Base."
o Specific POI categories such as petrol stations, repair shops, or truck stops can indicate "Refuelling/ Maintenance" or "Rest."

o Stops with no clear POI or land use match, or very short durations, might be categorised as "Traffic Wait" or "Unidentified."
This rule-based approach, while requiring careful definition of rules and thresholds, provides a robust framework for associating observed stops with likely freight activities.

3.6. Truck Activity Mode Clustering
To identify typical truck activity patterns, a two-step clustering method is applied to the processed truck tour data. This method is particularly suitable for large datasets with mixed data types (numerical and categorical). The clustering process involves:

a) **Feature Selection:** Key features representing the characteristics of each truck's activity tour are selected for clustering. These features include:

- o **Total Daily Travel Distance:** A measure of the scale of operation.
- o **Total Daily Travel Duration:** Reflecting time spent on the road.
- o **Number of Stops per Day:** Indicating the complexity of the tour.
- o **Average Stop Duration:** Revealing the nature of activities at stops (quick deliveries vs. lengthy loading/unloading).
- o **Proportion of Intra-city vs. Inter-city Trips:** Distinguishing between local and regional operations. This is determined by analysing if origin and destination points of trips fall within or outside Shanghai's administrative boundaries.
- o **Number of Unique Hub Stops:** Defined as frequently visited locations (e.g., logistics parks, distribution centres) that serve as primary operational bases.
- o **Distribution of Inferred Activity Purposes:** Proportions of different activity types (e.g., proportion of loading/unloading stops, delivery stops, rest stops).

b) **Two-Step Clustering Algorithm:**

o **Pre-clustering (Distance-Based):** In the first step, a distance-based clustering algorithm (e.g., agglomerative hierarchical clustering or a custom grid-based approach) is used to group similar observations into pre-clusters. This step is efficient for handling large datasets by reducing the number of individual instances.
o **Clustering (Model-Based/Hierarchical):** In the second step, a more sophisticated clustering algorithm (e.g., hierarchical clustering or K-means on the pre-clusters) is applied. This step aims to identify the optimal number of clusters and define the distinct activity modes. The optimal number of clusters is often determined using statistical criteria such as the Bayesian Information Criterion (BIC) or silhouette scores.
The output of the clustering process is a set of distinct truck activity modes, each characterised by a unique profile based on the selected features. These modes represent different operational strategies and roles of freight trucks in the urban logistics system. The results of this clustering will form the basis for differentiated policy recommendations.

4. Results and Discussion
This section presents the findings from the data analysis, including the characterisation of truck travel, the identified activity purposes, and the derived truck activity modes.

4.1. Characterisation of Truck Travel in Shanghai
The analysis of high-frequency GPS data from heavy freight trucks in Shanghai reveals several key characteristics of their travel patterns:

- **Trip Length Distribution:** The majority of truck trips within Shanghai are relatively short, reflecting the high density of urban activities and the prevalence of last-mile and intra-city distribution. A significant proportion of trips fall within the 10-50 km range, indicating intensive urban logistics operations. However, a noticeable tail exists for longer trips (over 100 km), representing inter-city or regional freight movements that connect Shanghai with its surrounding provinces (As shown in **Figure 4.1.1.**).

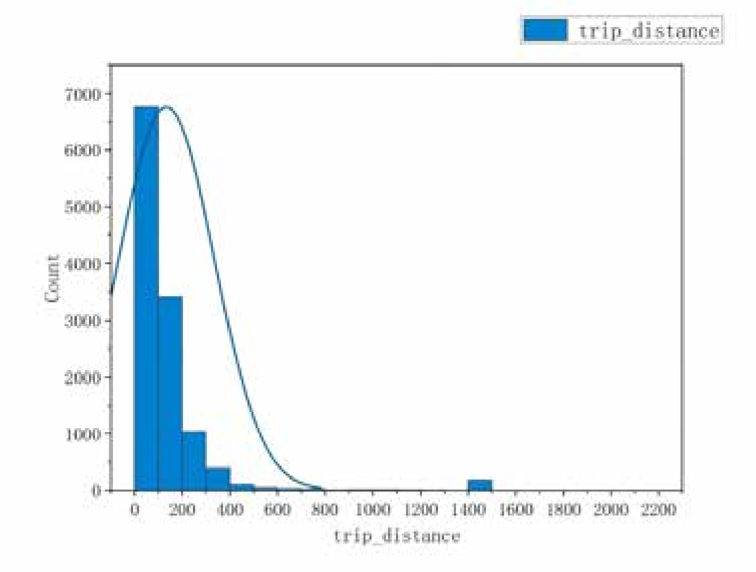

Figure 4.1.1. Distribution Map of Travel Distances (Image source: Self-drawn)

- **Trip Duration:** While trip lengths might be moderate, trip durations are often extended due to urban congestion, traffic restrictions, and the time spent at stop points for loading/unloading. The average speed of trucks within the city proper is generally low, especially during peak hours (As shown in **Figure 4.1.2.**).

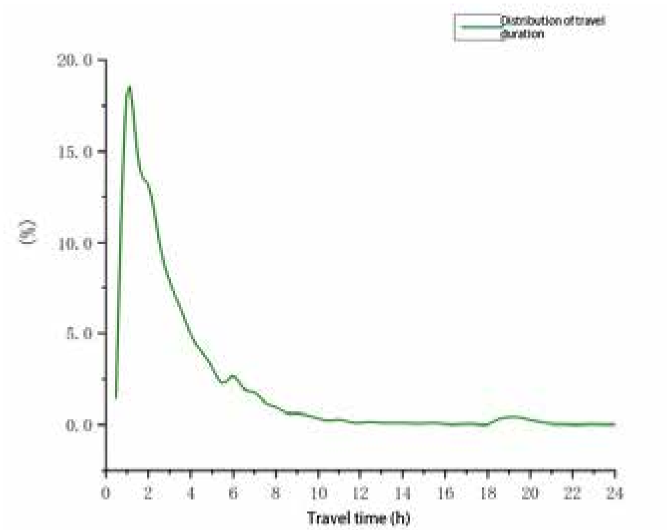

Figure 4.1.2. Travel duration distribution map (Image source: Self-drawn)

- **Stop Frequency and Duration:** Trucks exhibit a high frequency of stops, particularly those engaged in urban distribution. The duration of these stops varies significantly. Short stops (e.g., 15-30 minutes) are typical for quick deliveries or drop-offs, while longer stops (e.g., 1-3 hours or more) are associated with major loading/unloading operations at warehouses, logistics parks, or industrial facilities.
- **Spatial Distribution of Activities:** Truck activities are heavily concentrated in specific areas:

    o **Logistics Hubs:** Areas with a high density of warehouses, distribution centres, and freight yards show intense activity, serving as major origins and destinations.
    o **Industrial Zones:** These areas are key for raw material input and finished goods output.
    o **Commercial Districts and Wholesale Markets:** Represent significant destinations for deliveries, often involving multiple stops.
    o **Port Areas:** For Shanghai, port-related drayage is a distinct and high-volume activity, involving movements between ports and inland logistics facilities.

- **Time-of-Day Patterns:** Heavy truck movements often exhibit distinct diurnal patterns influenced by urban traffic regulations. A significant portion of inter-city movements occurs during off-peak hours or at night to avoid daytime traffic restrictions. Intra-city deliveries, while also affected by restrictions, might have more dispersed patterns depending on the type of goods and recipient requirements. There is usually a surge in activity during early mornings and late evenings (As shown in **Figure 4.1.3.**).

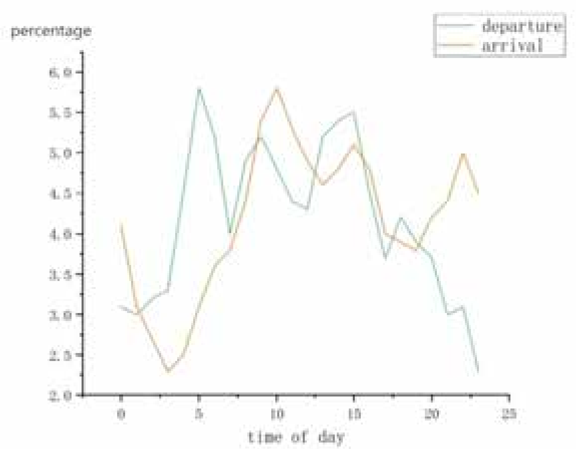

Figure 4.1.3. Travel time distribution map (Image source: Self-drawn)

These characteristics highlight the dynamic and constrained operational environment for freight trucks in a high-density urban context like Shanghai.

4.2. Inferred Truck Activity Purposes

Based on the integration of GPS data with land use and POI information, the primary purposes of truck activities at identified stop points were inferred and broadly categorised. The findings indicate a diverse range of activities beyond simple pick-up and delivery:

- **Loading/Unloading at Industrial/Warehousing Facilities (approx. 40%):** This category represents the most frequent activity, occurring at factories, large warehouses, and logistics parks. These stops are typically longer, indicating significant cargo handling.
- **Delivery to Commercial/Retail Outlets (approx. 25%):** These stops are often shorter and more numerous, characteristic of last-mile delivery to shops, restaurants, or smaller businesses within commercial zones.
- **Transshipment/Cross-docking (approx. 15%):** Occurring primarily at distribution centres or logistics hubs, these stops involve the transfer of goods between different trucks or modes of transport. This highlights the multi-stage nature of many freight operations.
- **Driver Rest/Personal Activity (approx. 10%):** These stops, often at designated rest areas, service stations, or even residential areas, reflect non-freight specific activities essential for driver well-being and regulatory compliance.
- **Vehicle Maintenance/Refuelling (approx. 5%):** Stops at petrol stations, repair shops, or maintenance depots.
- **Waiting/Congestion-related Stops (approx. 5%):** These stops are often involuntary, due to traffic queues, entry/exit delays at facilities, or waiting for appointments. While not a "purpose" in the productive sense, they represent significant operational time.
- **Other/Unidentified:** A small percentage of stops where a clear purpose could not be definitively inferred from the available data.

The distribution of these inferred purposes underscores the complexity of urban freight, involving not only the movement of goods but also associated logistical, regulatory, and human-factor considerations.

4.3. Classification of Truck Activity Modes

The two-step clustering algorithm, applied to the selected features of truck activity tours, successfully identified distinct activity modes. The analysis revealed two main categories of truck activities, further subdivided into a total of five sub-categories (The proportion of each subcategory is shown in **Figure 4.3.1.**), each with unique characteristics, as shown in **Tables 4.3.1. -4.3.3.**:

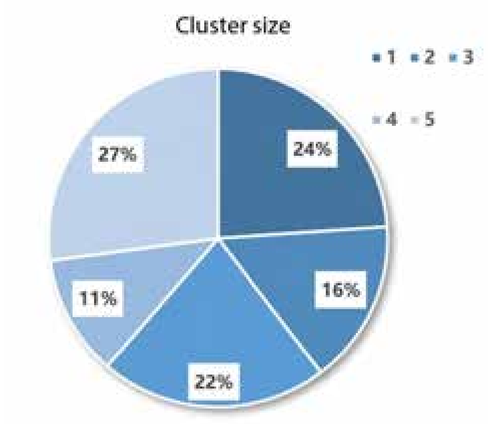

Figure 4.3.1. Clustering modeling results (Image source: Self-drawn)

Table 4.3.1. Characteristics of Travel Distances and Expressway Usage Proportions of Different Categories (Source: Self-drawn by the Author)

Average value		Trip-distance		Highway-ratio	
		Standard deviation	Average value	Standard deviation	
Category	1	42.89	29.18	0.49	0.33
	2	112.66	77.12	0.68	0.27
	3	167.06	118.54	0.57	0.33
	4	328.54	480.82	0.59	0.34
	5	116.36	95.21	0.51	0.32
	Combination	133.82	200.44	0.56	0.33

Table 4.3.2. Characteristics of Different Types of Travel Purposes (Source: Self-drawn by the Author)

Frequency 0		Light industry		Heavy industry		Transportation, warehousing and postal services		Wholesale and retail trade	
		1	0	1	0	1	0	1	
Cate-gory	1	2871	0	2871	0	2871	0	0	2871
	2	1484	403	1887	0	1887	0	1160	727
	3	2609	0	2609	0	2609	0	0	2609
	4	1350	42	163	1229	1379	13	1307	85
	5	2085	1170	3255	0	2145	1110	3255	0
	To-tal	10399	1615	10785	1229	10891	1123	5722	6292

Table 4.3.3. Stopping Characteristics of Different Types of Large Transportation Hubs (Ports, railway stations, etc.) (Source: Self-drawn by the Author)

Frequency		hub			cross-type	
0		1	2	0	1	
Category	1	2871	0	0	0	2871
	2	0	1843	44	1490	397
	3	2609	0	0	2609	0
	4	1218	174	0	1053	339
	5	2986	265	4	2036	1219
	Total	9684	2282	48	7188	4826

Main Category 1: Localised Urban Freight Operations This category predominantly involves trucks operating within the metropolitan area, characterised by shorter travel distances, higher stop frequencies, and intense interaction with the urban fabric.

- **Sub-category 1.1: Multi-Stop Urban Distribution (e.g., "City Courier")**
    - o **Characteristics:** Short daily travel distances (e.g., 50-150 km), high number of stops (e.g., 10-20+ per day), short average stop duration (e.g., 15-45 minutes), almost exclusively intra-city trips. Few, if any, hub stops, typically starting from a single depot. The specific example is shown in **Figure 4.3.2.**.
    - o **Inferred Purpose Dominance:** Delivery to Commercial/Retail Outlets, Collection from businesses.
    - o **Operational Profile:** These trucks are typically engaged in last-mile delivery of varied goods (e.g., parcels, perishables, retail supplies) to multiple addresses within a specific urban zone. Their efficiency is highly dependent on route optimisation and quick turnaround times at delivery points.

Figure 4.3.2. Pattern 1.1 Representative trip Trajectory Analysis Diagram
(Image source: Self-drawn)

- **Sub-category 1.2: Dedicated Industrial/Commercial Haulage (e.g., "Industrial Shuttle")**
    - o **Characteristics:** Moderate daily travel distances (e.g., 100-300 km), moderate number of stops (e.g., 2-8 per day), longer average stop duration (e.g., 1-3 hours), primarily intra-city but potentially short inter-district trips. Often involves repeated trips between a limited set of industrial or large commercial hubs. The specific example is shown in **Figure 4.3.3.**.

o **Inferred Purpose Dominance:** Loading/Unloading at Industrial/Warehousing Facilities, Transshipment.
o **Operational Profile:** These trucks specialise in transporting goods between specific industrial sites, large warehouses, or major commercial distribution centres. Examples include moving raw materials to factories, finished goods from factories to distribution centres, or large-volume deliveries to hypermarkets. Their routes are often fixed or semi-fixed.

Figure 4.3.3. Pattern 1.2 Representative trip Trajectory Analysis Diagram
(Image source: Self-drawn)

- **Sub-category 1.3: Differentiated Intra-city Logistics (e.g., "Service Provider")**
  o **Characteristics:** Highly variable daily travel distances (e.g., 30-200 km), low to moderate number of stops (e.g., 1-5 per day), stop durations can vary significantly (e.g., 30 minutes to several hours), entirely intra-city. May include stops for specific services or irregular deliveries. The specific example is shown in **Figure 4.3.4.**.
  o **Inferred Purpose Dominance:** Could be a mix of specialised deliveries, waste collection, construction material transport, or service-related stops (e.g., maintenance, utilities).
  o **Operational Profile:** This heterogeneous group includes trucks performing specialised tasks not directly tied to general merchandise distribution. Examples include construction material delivery, waste management, or technicians' vehicles carrying heavy equipment. Their routes are less predictable and more demand-driven.

Figure 4.3.4. Pattern 1.3 Representative trip Trajectory Analysis Diagram
(Image source: Self-drawn)

Main Category 2: Regional/Inter-city Freight Operations This category comprises trucks primarily engaged in long-distance movements connecting Shanghai with other cities or regions, often involving fewer stops within the city itself, but longer hauls.

- **Sub-category 2.1: Long-Haul Inter-city (e.g., "Regional Connector")**
  - o **Characteristics:** Long daily travel distances (e.g., 300-800+ km), very few stops (e.g., 1-2 per day), typically long stop durations at origin/destination hubs (e.g., 3-8 hours), high proportion of inter-city travel. Origin and destination are often outside Shanghai, with a single stop within Shanghai for loading/unloading at a major logistics hub. The specific example is shown in **Figure 4.3.5.**.
  - o **Inferred Purpose Dominance:** Loading/Unloading at Logistics Hubs, Transshipment.
  - o **Operational Profile:** These trucks are the backbone of regional and national supply chains, transporting goods between major cities. Their time is primarily spent on the road, with concentrated activities at large-scale distribution centres or intermodal terminals. They are heavily impacted by highway regulations and cross-provincial logistics networks.

Figure 4.3.5. Pattern 2.1 Representative trip Trajectory Analysis Diagram
(Image source: Self-drawn)

- **Sub-category 2.2: Hub-and-Spoke Regional (e.g., "Regional Distributor")**
  - o **Characteristics:** Moderate to long daily travel distances (e.g., 200-500 km), moderate number of stops (e.g., 2-5 per day), variable stop durations, a mix of inter-city (to/from a central hub) and intra-city (distribution from the hub) trips. Characterised by a primary hub stop within Shanghai and subsequent distribution to peripheral urban or suburban areas. The specific example is shown in **Figure 4.3.6.**.
  - o **Inferred Purpose Dominance:** Transshipment/Distribution from Hub, followed by Delivery to Commercial/Retail Outlets or Industrial Facilities.
  - o **Operational Profile:** These trucks operate within a hub-and-spoke model, where a major logistics centre in Shanghai serves as a consolidation or break-bulk point. Goods arrive from other cities, are processed at the hub, and then distributed to destinations within Shanghai or its immediate hinterland, or vice versa.

Figure 4.3.6. Pattern 2.2 Representative trip Trajectory Analysis Diagram
(Image source: Self-drawn)

Key Differences and Insights:
The classification highlights significant differences across the identified modes:

- **Travel Distance:** Ranges from short (Sub-category 1.1) to very long (Sub-category 2.1), indicating different operational scales.
- **Number of Stops:** Differentiates between point-to-point transfers and multi-point distribution.
- **Hub Dependence:** Some modes (Sub-category 2.2) are highly dependent on major logistics hubs, while others (Sub-category 1.1) operate more autonomously from a single base.
- **Intra-city vs. Inter-city Focus:** This is a fundamental discriminator, with distinct policy implications for local versus regional traffic management.

These distinct profiles underscore the limitations of "one-size-fits-all" urban freight policies. Recognising these activity modes provides a robust foundation for developing targeted and effective policy interventions.

5. Management Recommendations and Policy Implications
The detailed understanding of truck activity modes derived from this study offers a unique opportunity to refine urban freight management policies in Shanghai, moving towards a more nuanced and inclusive approach. Current policies often impose uniform restrictions that disproportionately affect certain freight operations while failing to adequately address the specific challenges posed by others. Based on the identified two main categories and five sub-categories of truck activities, the following targeted management suggestions are proposed:

5.1. Tailored Regulations for Localised Urban Freight Operations
The "Localised Urban Freight Operations" category (Sub-categories 1.1, 1.2, 1.3) represents the majority of heavy truck movements within the immediate urban area, directly impacting daily urban life.

- **For Multi-Stop Urban Distribution (Sub-category 1.1 – "City Courier"):**
  - o **Challenge:** High stop frequency, short distances, often operating in congested commercial/residential areas. Existing blanket time-window restrictions can severely limit their operational efficiency.
  - o **Recommendation:** Implement more flexible and granular time-window restrictions. Instead of broad bans, consider designated delivery windows for specific zones (e.g., pedestrian streets) or allow access during certain off-peak hours for smaller, cleaner trucks. Promote the use of dedicated urban loading/unloading zones that are clearly marked and enforced, potentially equipped with smart sensors to manage usage. Explore micro-consolidation centres at the edge of high-density areas to reduce the number of large trucks making individual stops.
  - o **Policy Focus:** Optimising last-mile delivery efficiency and minimising urban disruption.

- **For Dedicated Industrial/Commercial Haulage (Sub-category 1.2 – "Industrial Shuttle"):**
  - o **Challenge:** Regular, heavy-volume movements between fixed points, often requiring access to industrial parks and large commercial complexes. These routes might intersect with general traffic, contributing to congestion.
  - o **Recommendation:** Develop dedicated freight corridors or preferential routes for these regular high-volume movements, especially connecting industrial zones with major logistics hubs or arterial roads. Implement intelligent traffic signal priority systems for heavy trucks on these designated routes where feasible. Consider differentiated access permits based on destination and frequency, rather than blanket restrictions.
  - o **Policy Focus:** Ensuring efficient supply chain connectivity for industries and large businesses, and mitigating their impact on general traffic flow.
- **For Differentiated Intra-city Logistics (Sub-category 1.3 – "Service Provider"):**
  - o **Challenge:** Diverse operations, often unpredictable routes, and varied cargo types (e.g., construction waste, specialised equipment). Their impact on traffic can be sporadic but significant.
  - o **Recommendation:** Categorise and regulate based on cargo type and vehicle purpose where appropriate. For instance, specific routes or disposal sites for construction waste trucks. For service vehicles, consider issuing special permits for access during restricted hours if their work is critical and time-sensitive (e.g., utility repairs). Promote technology adoption (e.g., dynamic routing, real-time communication) to optimise their movements.
  - o **Policy Focus:** Facilitating essential urban services while managing their varied impacts.

5.2. Strategic Management for Regional/Inter-city Freight Operations

The "Regional/Inter-city Freight Operations" category (Sub-categories 2.1, 2.2) plays a crucial role in connecting Shanghai to the broader national and international supply chains, but their long hauls and large sizes pose different challenges, particularly at urban entry points.

- **For Long-Haul Inter-city (Sub-category 2.1 – "Regional Connector"):**
  - o **Challenge:** Primarily concerned with efficient movement between major urban centres, often operating on highways, but needing smooth access to and from large logistics hubs within Shanghai. Time-window restrictions at urban entry points can lead to bottlenecks.
  - o **Recommendation:** Implement "big data informed, flexible traffic restrictions." Instead of fixed time-window bans, use real-time traffic data, weather conditions, and predicted demand to dynamically adjust access times to major logistics parks or expressways leading out of the city. Promote the use of off-peak hours and night-time for these movements. Invest in intelligent truck parking facilities at the urban periphery to manage waiting times before entry.
  - o **Policy Focus:** Enhancing regional connectivity and reducing congestion at urban gateways.
- **For Hub-and-Spoke Regional (Sub-category 2.2 – "Regional Distributor"):**
  - o **Challenge:** A combination of long-haul movements to a central hub and subsequent intra-city distribution. This requires efficient transshipment and effective last-mile delivery from the hub.
  - o **Recommendation:** Prioritise investment in and optimisation of urban logistics hubs (e.g., multi-storey warehouses, automated sorting facilities) that serve as critical interfaces for these operations. Policies should encourage the use of smaller, cleaner vehicles for the intra-city distribution leg from these hubs. Facilitate intermodal transfers at these hubs where possible (e.g., rail or water links). Provide clear, efficient routes from highways to these hubs.
  - o **Policy Focus:** Streamlining the interface between long-haul freight and urban distribution, promoting sustainable last-mile solutions.

5.3. Cross-Cutting Policy Considerations

Beyond mode-specific recommendations, several overarching policy directions emerge:

- **Leveraging Big Data and AI:** The success of these differentiated policies relies heavily on continuous data collection and analysis. Shanghai should invest further in smart city infrastructure to gather real-time freight data, use AI for predictive analytics (e.g., congestion hotspots, optimal delivery times), and support dynamic policy adjustments.
- **Green Freight Initiatives:** Differentiated policies can also be used to incentivise greener freight vehicles. For example, preferential access or reduced charges for electric or low-emission trucks, particularly for urban distribution (Sub-category 1.1).

- **Collaboration with Industry:** Effective policy implementation requires strong collaboration with logistics companies, industry associations, and drivers. Pilot projects and feedback mechanisms can help refine policies to ensure they are practical and beneficial for all stakeholders.
- **Infrastructure Investment:** Targeted investment in critical freight infrastructure, such as multi-functional urban logistics hubs, dedicated truck parking, and improved last-mile delivery infrastructure, is essential to support the proposed policy changes.
- **Driver Welfare:** Any policy reforms should also consider the impact on truck drivers, including access to rest facilities, clear communication of regulations, and support for their working conditions.

By moving away from simplistic, uniform rules, Shanghai can develop an urban freight management system that is more responsive to the diverse needs of freight operators, more efficient in its use of urban space, and ultimately, more conducive to a sustainable and prosperous urban environment. This study provides the empirical foundation for such a transformative shift.

6. Conclusion

This study embarked on a comprehensive investigation into urban freight mobility in Shanghai, leveraging extensive high-frequency GPS trajectory data from heavy trucks. The research successfully moved beyond aggregate observations to infer the underlying activity patterns and purposes of individual truck movements, providing a micro-perspective crucial for effective urban freight management.

Through rigorous data processing, including precise stop point identification and path map matching, the fundamental characteristics of truck travel in a high-density urban environment were thoroughly detailed. The integration of land use and Points of Interest data allowed for a robust inference of activity purposes at various stop locations, revealing the complex interplay of industrial, commercial, and logistical functions.

The application of a two-step clustering method was pivotal in identifying distinct truck activity modes. The study successfully classified freight truck operations into two main categories: “Localized Urban Freight Operations” and “Regional/Inter-city Freight Operations,” which were further subdivided into five specific sub-categories. These categories exhibit significant differences in key operational attributes, such as daily travel distance, the number and nature of stops, and the predominant travel scope (intra-city versus inter-city). This differentiation underscores the inherent heterogeneity of urban freight and highlights the inadequacy of traditional “one-size-fits-all” policy approaches.

Based on these findings, the study proposes a suite of targeted management recommendations. These suggestions advocate for a paradigm shift towards more inclusive and differentiated urban freight policies. For instance, specific requirements are suggested for short-distance, multi-stop urban distribution trucks, acknowledging their unique challenges in congested areas. Simultaneously, the study proposes the implementation of flexible traffic restrictions for long-haul and regional trucks, dynamically informed by real-time big data, rather than rigid, static time windows.

The insights generated by this research pave the way for the development of innovative, localised urban freight systems in Shanghai and potentially other high-density cities. By understanding and addressing the specific needs and operational patterns of different freight activity modes, urban planners and policymakers can foster a freight ecosystem that is not only more efficient and cost-effective for businesses but also more harmonious with urban life, contributing to reduced congestion, lower emissions, and improved quality of life for residents. Future research could explore the integration of real-time traffic conditions into activity mode prediction and the socio-economic impacts of implementing these differentiated policies.

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