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Revealing the impacts of COVID-19 pandemic on intercity truck transport: New insights from big data analytics

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Abstract

Intercity truck transport emerged as a crucial lifeline for maintaining city operations during COVID-19 pandemic. Understanding pandemic-imposed impacts on intercity truck transport can inform policymakers in crafting more effective strategies for future crises and disruptions. However, to our best knowledge, previous research predominantly focused on freight movements under normal circumstances. Due to the data limitation, the pandemic-related studies commonly relied on freight survey and focused on specific industries, which cannot capture the full spectrum of factors influencing freight trip generation (FTG) during the pandemic. Here, a novel dataset capturing large-scale individual truck movements during the COVID-19 pandemic is provided. By leveraging the mobility dataset, pandemic-induced changes in truck transport demand structure are quantified using spatial statistical methods. Furthermore, an interpretable machine learning framework for intercity freight demand estimation is developed, revealing the complex interplay of factors that influence and shape the behavior shifts of intercity truck transport systems due to the pandemic outbreak. The findings suggest significant changes in various factors influencing intercity truck movements across local and broader regions, emphasizing city-specific challenges amidst pandemic. The developed FTG model could serve as a tool to predict freight demand between cities for future crises and to support policymaking in the practice of freight management.

Keywords: intercity truck transport, COVID-19 pandemic, big data analytics, machine learning

1. Introduction

The outbreak of the COVID-19 pandemic led to a global crisis, prompting nations worldwide to implement stringent measures aimed at curbing the spread of the virus. Among these measures, city lockdowns and various control strategies were commonly employed to mitigate the transmission of the virus among populations, especially in the early stage. While these travel restriction policies limited the movement of residents, intercity truck transport swiftly emerged as an indispensable artery for normal city operations (Fang et al., 2023). Trucks played a vital role in transporting essential goods, traversing borders, and connecting regions especially during the pandemic crisis. They formed the backbone of supply chains, ensuring that critical medical supplies, food, and necessities continued to reach communities in need(Yang et al., 2024a). The COVID-19 outbreak significantly influenced the demand structure and intrinsic driving factors of intercity truck transport, leading to notable shifts in freight movement patterns (Beckers et al., 2022). Understanding impacts of COVID-19 pandemic on intercity truck transport can inform policymakers in crafting effective strategies to support the resilience of freight transport networks.

Intercity truck movements are commonly driven by a variety of factors, including economic activities, population density, industrial distribution and the availability of infrastructure (Yang et al., 2023a). These factors shape the demand of freight transport, influencing how and where trucks are moved between cities. Due to the outbreak of the COVID-19 pandemic, the driving factors of truck movements may have undergone changes, as evidenced by increased e-commerce activity (Soava et al., 2022), altered consumer behavior (Ho et al., 2021), and shifts in supply chain operations (Fu et al., 2022), which in turn impacted the volume and frequency of freight trips. Understanding the transformation of these driving factors and accurately predicting the volume of truck movements are critical aspects of freight planning in the post-pandemic era.

Understanding the impacts of the COVID-19 pandemic on intercity truck transport presents several challenges. The pandemic has introduced unprecedented variability in freight demand, complicating efforts to accurately model and predict truck movements. Traditional freight trip generation (FTG) models (Al-Battaineh et al., 2005; de Oliveira et al., 2022; Holguin-Veras et al., 2011; Jesus et al., 2020; Middela and Ramadurai, 2024; Sorratini and Smith Jr, 2000), which rely on historical data and stable economic patterns, may not fully capture the new dynamics introduced by the pandemic, such as sudden spikes in e-commerce or shifts in essential goods transportation. Additionally, the interplay between the pandemic's effects and pre-existing factors, such as economic fluctuations, changes in consumer behavior, and infrastructure constraints, adds layers of complexity to the analysis. To address these challenges and enhance the accuracy of FTG models in the context of the pandemic, integrating big data analytics and machine learning technologies offers promising solutions. However, due to the unavailability of high-resolution data on truck movements during the pandemic outbreak, the intricate factors shaping FTG dynamics amid pandemic especially at national scale remains underexplored.

To fill in the gaps, a novel GPS dataset of more than 2.7 million trucks was collected before and after the outbreak of the COVID-19 pandemic in China, along with a wide range of geographic and industrial features. By leveraging the large-scale GPS data, the spatiotemporal patterns of intercity truck movements were analyzed to understand the impact of the COVID-19 pandemic on freight transport. Specifically, the pandemic-induced disruptions were examined to determine their influence on truck flows across different regions, with key shifts in transportation demand dynamics being identified. Spatial statistical methods were employed to detect changes in truck movement patterns, providing insights into the varying degrees of impact across different geographic areas and industrial sectors. Furthermore, an interpretable machine learning framework was developed to model FTG under the unique conditions imposed by the pandemic. This framework integrates a wide array of geographic, economic, and industrial features to accurately capture the complex factors driving intercity truck transport during the pandemic. The findings highlight the need for adaptive strategies that can respond to sudden disruptions, ensuring the resilience of supply chains during future crises.

The work contributes to literature in four ways. (1) A novel data source of large-scale truck movements during the COVID-19 pandemic is provided, with a more granular analysis for intercity transport systems. (2) Changes in the structure of intercity truck transport demand are quantified, providing a comprehensive understanding of the freight demand dynamics under the COVID-19 outbreak. (3) An interpretable machine learning framework for intercity freight demand estimation is developed. (4) The complex interplay of factors that influenced and shaped the behavior of intercity truck transport systems during the COVID-19 crisis is revealed , along with potential implications for freight transport systems management.

The remainder of this paper is organized as follows: **Section 2** gives the literature review. **Section 3** provides data sources and the methods of quantifying the changes in structure of intercity truck transport demand, constructing and explaining FTG model. **Section 4** analyzes the research results. **Section 5** discusses practical implications derived from research findings. **Section 6** at the end, offers concluding insights.

2. Literature Review

2.1. Freight trip generation (FTG) modeling

Modern transportation planning relies on the development of demand and supply models to effectively manage transportation systems and infrastructure. FTG models, as a demand-side component, serve as fundamental tools for forecasting and analyzing truck movements across regions (Tavasszy and De Jong, 2013). Previous studies have identified variables that explain FTG, encompassing economic (Cheah et al., 2021; Holguin-Veras et al., 2011; Madar et al., 2021; Pani et al., 2023; Venkadavarahan and Marisamynathan, 2022), land use (De Bakshi et al., 2020; Gonzalez-Feliu and Peris-Pla, 2018; Holguín-Veras et al., 2012; Holguin-Veras et al., 2013; Lawson et al., 2012; Pani et al., 2019), and infrastructure factors (Al-Deek, 2001; Al-Deek and Trb; Trb, 2001; Alho and de Abreu e Silva, 2014, 2017; Davydenko et al., 2012; Dhonde and Patel, 2021; González-Calderón et al., 2016). For instance, Holguín-Veras et al. (2019) emphasized the direct correlation between socio-economic descriptors (including population, establishments and employment) and the volume of freight activities, where economic growth drives up demand for goods, thus increasing the frequency of freight trips. They estimated the freight rates for selected descriptors to predict truck trips between regions in different cities. Lawson et al. (2012) found that commercial, industrial, and mixed-use zones generate more freight trips than residential zones. The spatial distribution of these zones impacts the volume and direction of freight trips. Their research highlights the importance of considering zoning regulations and land use planning in FTG analysis to manage urban freight effectively. Similarly, Venkadavarahan and Marisamynathan (2021) showed that efficient road networks could reduce travel time and cost, encouraging more frequent freight trips. By incorporating these explanatory variables, FTG models, including trip rate models (Holguin-Veras et al., 2011; Jesus et al., 2020; Kulpa, 2013), regression models (Alho and de Abreu e Silva, 2014; Bastida and Holguin-Veras, 2009; de Oliveira et al., 2022; Middela and Ramadurai, 2024) and Input-Output models (Al-Battaineh et al., 2005; Sorratini and Smith Jr, 2000) have been developed to estimate freight movements across regions and cities.

2.2. The impact of COVID-19 pandemic on FTG modeling

During the period of COVID-19 pandemic, the dynamics of freight movements experienced significant shifts due to various disruptions and changes in demand patterns (Arellana et al., 2020; Gonzalez et al., 2022). The pandemic led to increased e-commerce activity (Soava et al., 2022), altered consumer behavior (Ho et al., 2021), and changes in supply chain operations (Fu et al., 2022), which in turn impacted the volume and frequency of freight trips. These changes necessitated adjustments of FTG modeling to capture the evolving landscape. Previous studies have conducted explorations into the impacts of the COVID-19 pandemic on freight transport and logistics. However, these investigations have often been based on survey data focused on specific industries or regions. For instance, Beckers et al. (2022) utilized household surveys originating from the "E-commerce in Belgium 2016" questionnaire, which was commissioned by the Belgian retail federation Comeos to identify online shopper behaviors. This research focused on understanding how the rise in online shopping especially in pandemic period has influenced the frequency and volume of residential freight trips. Venkadavarahan and Marisamynathan (2023) used data from an Establishment Based Freight Survey (EBFS) collected from an Indian smart city, comprising 1,793 samples. The research aimed to assess the causal interrelationship of Supply Chain Characteristics (SCC) and their impact on freight trip activity between intermediate and pure receiver establishments. de Souza and Mátrai (2022) gathered data from various traffic collection points in Budapest. They proposed adjustments to an existing four-step transportation model, involving incorporating contextual explanatory variables and recalibrating model parameters to reflect the effects of the pandemic on trip generation and distribution patterns. Moreover, Fadhlansyah (2022) investigated the factors influencing FTG for online shopping and home deliveries during COVID-19 pandemic. Data for the study were collected through questionnaires distributed to 273 residents in the Jabodetabek area in Indonesia.

While previous studies have provided valuable insights into the effects of the COVID-19 pandemic on freight transport, they have focused on specific industries or regions and relied on survey data, which cannot capture the full spectrum of factors influencing FTG during the pandemic.

2.3. Big data analytics and methods

The advent of big data analytics has introduced new opportunities to enhance the precision and adaptability of FTG models, particularly through the use of GPS data (Comendador et al., 2011; Yang et al., 2023a). GPS data provide high-resolution spatial and temporal information on vehicle movements, enabling the detailed tracking of freight trips. This granularity allows researchers and planners to observe patterns in freight transportation that were previously obscured by aggregate survey data.

Machine learning and artificial intelligence (AI) are central to leveraging GPS data in FTG modeling. Techniques such as neural networks (Lafta and Ismael, 2022), decision trees (Alho and de Abreu e Silva, 2017), random forests (Du and Yin, 2024), and support vector machines (Liu et al., 2006) have been applied to analyze large datasets, identifying complex relationships between variables that traditional statistical methods might overlook. Recently, numerous studies (Akter and Hernandez, 2023; Chen and Liu, 2013; El Ouadi et al., 2020; Javanmard et al., 2024; Ludowieg et al., 2022; Saeed et al., 2023; Salais-Fierro and Martinez, 2022; Uddin et al., 2023; Xie and Huynh, 2010) have focused on machine learning techniques for estimating freight traffic volume and the origin-destination (OD) matrix. Furthermore, the progress in hardware and algorithms, coupled with the demand for accurate trip generation, has led to the development of more advanced techniques, such as deep learning and reinforcement learning models, as summarized in the review articles (George and Santra, 2020; Jiang and Luo, 2022; Tedjopurnomo et al., 2022; Yin et al., 2022). In addition to improving the accuracy of FTG models, the use of machine learning can also enhance the interpretability and usability of these models. Techniques such as feature importance analysis, SHapley Additive exPlanations (SHAP) values (Lundberg and Lee, 2017), and the Local Interpretable Model-agnostic Explanations (LIME) (Ribeiro et al., 2016) can help identify the key factors driving truck movements. These tools can highlight which variables, such as distance to distribution centers or road network density, are most influential in determining freight trip patterns (Yang et al., 2023a).

In summary, while substantial progress has been made in FTG modeling through traditional methods and machine learning techniques, a significant gap in current research is the limited exploration of how the COVID-19 pandemic has influenced the performance and accuracy of machine learning models in FTG analysis. The pandemic has led to substantial shifts in freight patterns due to increased e-commerce, altered consumer behaviors, and disrupted supply chains. However, studies that specifically examine how these pandemic-induced changes impact machine learning-based FTG models are scarce.

3. Methodology and data

In the paper, the truck flows between cities are first obtained from a large-scale truck GPS dataset before and after the COVID-19 outbreak. The changes in the structure of intercity truck transport demand are then quantified using spatial statistical methods. An XGBoost-based intercity FTG model is constructed, and the tool of SHapley Additive exPlanations (SHAP) is employed to explain this model. Finally, based on the results, implications for city resilience, sustainability, and transport planning are provided. The methodology framework is illustrated in **Fig. 1**.

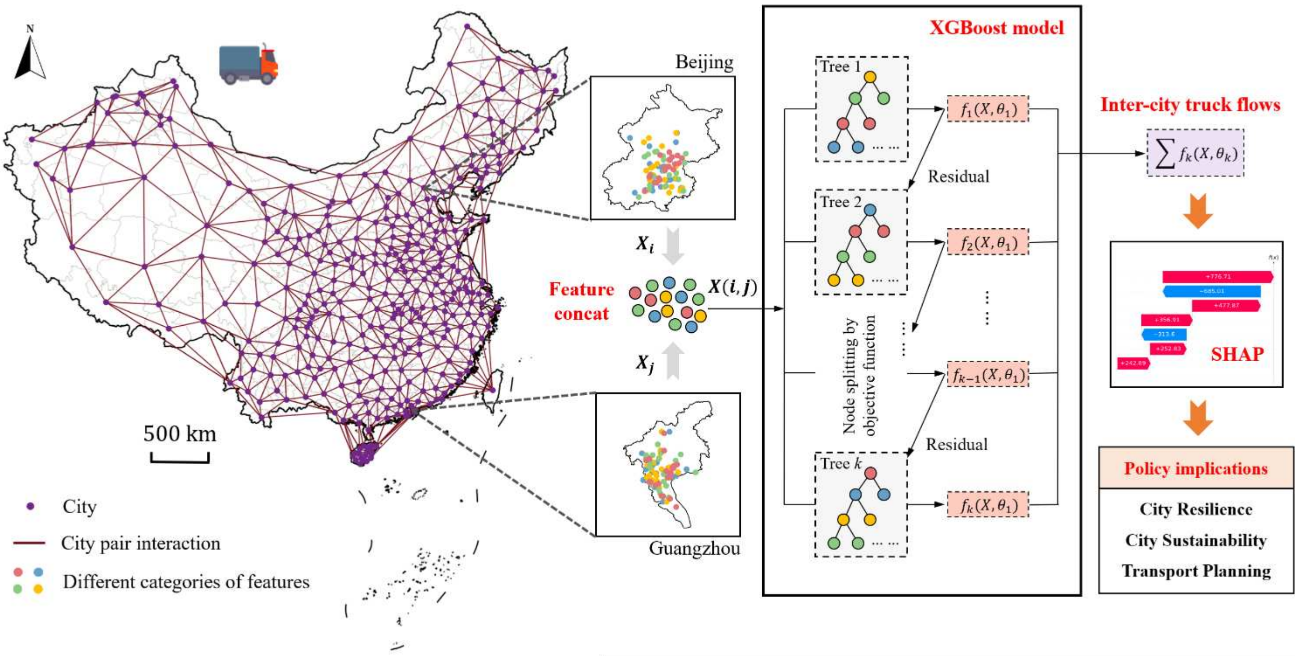

Fig. 1. Methodology framework.

3.1. Data sources and processing

In this study, three datasets were utilized to analyze intercity truck transport during the COVID-19 pandemic. First, truck GPS data, which include over 2.7 million truck trajectories in China, were used to capture truck movements before and after the pandemic lockdown. Second, freight POI data, which include points of interest related to freight activities, were employed to characterize the features and distribution of freight-related locations. Third, geographic data were provided to offer information on road networks and land uses, offering the spatial context of truck movements. By integrating these data sources, the aim was to obtain the truck flows between cities before and after the pandemic outbreak and to construct and explain the intercity FTG model.

3.1.1. Truck GPS data

The first reported instance of the COVID-19 outbreak occurred in Wuhan, China, with the city being officially placed under lockdown on January 23, 2020. To understand the impact of the COVID-19 outbreak, GPS trajectory data for 2.7 million trucks in China were collected for one week before and after January 23, 2020, i.e., the data span is from January 16, 2020, to January 29, 2020. The GPS dataset was obtained from the China Road Freight Supervision and Service Platform (https://www.gghypt.net/).This platform is an integrated system designed to oversee and enhance the efficiency of road freight operations throughout China (Yang et al., 2024b). It serves as a comprehensive platform that leverages technology, data, and logistics to monitor, manage, and optimize the transportation of goods via road networks across the country. This platform records the real-time geographic locations of all trucks in China. The collected dataset contains more than 2.7 million activated trucks, and the number of records is greater than 30 billion.

The GPS dataset is used to obtain truck flows between cities before and after the COVID-19 outbreak. To achieve this, the raw data is first preprocessed to handle erroneous and redundant information, and a data-driven intercity truck origin-destination (OD) identification method (Yang et al., 2022b) is employed to extract truck trips from GPS trajectories. In this method, truck trajectory characteristics are captured under the influence of GPS drift (i.e., the phenomenon where the GPS signal inaccurately reflects the true position of a GPS-enabled device) to identify truck stops from GPS data. Subsequently, the temporal characteristics of truck activities are analyzed, and valid trip ODs from truck stops are identified using freight-related locations data and highway network data. Using this method, consecutive trips for each truck are first extracted over the dataset span. The aggregated directed truck flows (i.e., truck transport demand) between all city pairs are then obtained for each week before and after the COVID-19 outbreak.

3.1.2. Freight POI data

Freight POI data are used to characterize the features of city freight locations, including freight-related companies, markets, and facilities. These features are used to construct and explain the intercity FTG model. The freight POI data were obtained through web crawling from Amap (https://lbs.amap.com/) utilizing the provided application programming interface (API). Within the Amap application, developers organize POIs in a hierarchical structure based on industry categories.

Three categories of POIs are chosen. Category one encompasses freight companies involved in metallurgy, medicine, telecommunication, construction, networking, trade, decoration, machinery, minerals, and factories. The second category comprises freight markets such as supermarkets, building material markets, home appliance markets, integrated markets, industrial parks, and agricultural bases. The third category includes freight facilities like transportation hubs (e.g., train stations, airports, and ports) and logistics nodes (e.g., warehouses and distribution centers).

3.1.3. Geographic data

Geographic data are used to characterize the features of city road networks and land uses. The data were derived from OpenStreetMap (https://www.openstreetmap.org/). According to the relevance to city truck activities (Yang et al., 2022a), three types of roads are selected, i.e., primary, secondary and motorway, and four classes of land uses, i.e., retail, residential, commercial, and industrial.

3.2. Quantifying the changes in structure of intercity truck transport demand

This section aims to characterize the pandemic-induced shifts in truck transport demand structure for two primary objectives. The first objective is to elucidate the spatial trends of truck transport demand reduction. The second objective is to uncover the truck transport demand reduction patterns between cities.

For the first objective, the reduction ratio in total truck transport demand of each city is calculated using aggregated directed truck flows before and after the COVID-19 outbreak. Spatial autocorrelation analysis (Bivand and Wong, 2018; Fan and Myint, 2014) is then employed to explore the geographic patterns of these reductions. The total truck transport demand of each city is defined as the sum of truck inflows and outflows of a city. The spatial autocorrelation analysis is a statistical method used to examine the degree of similarity or dissimilarity between nearby geographic locations in a dataset. Global Moran's I (Moran, 1950) and local indicators of spatial association (LISA) (Anselin, 1995) are employed for spatial autocorrelation analysis. Global Moran's I is used to assess the overall spatial clustering or dispersion of the reduction in truck transport demand across cities. This statistical method provides a single index value that indicates whether the reduction in demand exhibit clustering (values close to +1) or dispersion (values close to -1). A Moran's I value close to zero indicated a random spatial pattern. LISA analysis provides localized insights by pinpointing areas where reductions in demand are notably clustered, distinguishing between high-high (cities with high reductions surrounded by others with high reductions), low-low (cities with low reductions surrounded by others with low reductions), high-low, and low-high spatial outliers. The results of LISA analysis are commonly presented as Moran scatterplot (Xiao and Gong, 2022; Zhi et al., 2024), in which a positive correlation implies spatial clustering, i.e., nearby cities tend to have similar values. Furthermore, the reduction in total truck transport demand per population of each city is calculated, and the spatial autocorrelation is analyzed to understand the localized effects and variations related to population size of cities.

For the second objective, the reduction in bidirectional total truck flows $T_{ij}^{reduction}$ between each city pair, e.g., city i and j is first calculated. Subsequently, the statistical relationship between $T_{ij}^{reduction}$ and the population of cities i and j (denoted by POP_i and POP_j), the distance between city pair d_{ij} is explored. The goal is to uncover how these two critical factors, i.e., population size and geographical distance, contribute to shaping the alterations in truck transport demand between cities. Especially, the gravitational relationship between the truck transport demand reduction and these two critical factors is examined by analyzing the scaling law (Jia et al., 2023; Lin et al., 2023; Yang et al., 2023b) between $T_{ij}^{reduction}$ and $POP_i \cdot POP_j / d_{ij}$, i.e.,

$$T_{ij}^{reduction} \sim \left(\frac{POP_i \cdot POP_j}{d_{ij}}\right)^{\gamma}, \tag{1}$$

where γ is fitted exponent. The gravitational relationship suggests that truck transport demand reduction between two cities is positively associated with their populations and inversely related to the distance separating them.

3.3. Intercity freight trip generation (FTG) model

Next, an XGBoost-based intercity FTG model is built (see **Fig. 1**), aiming to firstly capture the intricate relationships between various city features and intercity truck movements before and after COVID-19 outbreak, and secondly provide a tool to predict freight demand between cities for future crises and disruptions.

The model is based on the XGBoost framework developed by Chen et al. (2016). XGBoost is renowned for its robustness in handling complex datasets and its capability to discern intricate patterns within them. It employs an ensemble learning technique, utilizing a collection of decision trees to iteratively refine predictions, enhancing both accuracy and generalizability. To construct the model, a comprehensive array of city features is integrated from freight POI data (see **Section 3.1.2**) and geographic data (see **Section 3.1.3**), capturing diverse aspects of city landscapes. These features encompass multifaceted dimensions such as freight company distributions, market characteristics, infrastructural facilities, road networks, land use compositions, and demographic attributes, as shown in **Table 1**.

26 features of each city *i* are collected and the feature vector $\boldsymbol{X_i}$ of dimension 26 is constructed. For the truck flows from city i to j, the feature vectors $\boldsymbol{X_i}$ and $\boldsymbol{X_j}$, and Euclidean distance d_{ij} between them are concatenated as an input sample $\boldsymbol{X}(i,j)$ of dimension 53. For each input sample $\boldsymbol{X}(i,j)$, two labels, i.e., aggregated actual truck flows before and after COVID-19 outbreak from city *i* to *j* are created. Input samples and corresponding two labels are used to train two XGBoost models respectively. The one is used to estimate the intercity truck transport demands before COVID-19 outbreak, and another one is used to estimate those after COVID-19 outbreak. To evaluate the performance of two models, the metric of root mean square error (RMSE) (Hyndman and Koehler, 2006) is used to measure the similarity between observed flows and generated flows by models. The *RMSE* metric is given by

$$RMSE = \sqrt{\frac{\sum_{i,j \neq i}(T_{ij}^{obs} - T_{ij}^{model})^2}{N_{pair}}}, \tag{2}$$

where N_{pair} is the number of city pairs, T_{ij}^{obs} is observed truck flows from city i to j, and T_{ij}^{model} is generated flows by the model.

Table 1. City features.

Category	Feature	Description
Freight companies (10 features)	*Metallurgy POIs*	Number of metallurgical companies in a city.
	Medicine POIs	Number of medical or pharmaceutical companies in a city.
	Telecommunication POIs	Number of telecommunication companies in a city.
	Construction POIs	Number of construction companies in a city.
	Network POIs	Number of network service providers in a city.
	Trade POIs	Number of trading companies in a city.
	Decoration POIs	Number of home decoration businesses in a city.
	Machinery POIs	Number of machinery manufacturers in a city.
	Mineral POIs	Number of mining-related sites in a city.
	Factory POIs	Number of factories in a city.
Freight markets (6 features)	*Industry-park POIs*	Number of industrial parks or zones in a city.
	Supermarket POIs	Number of supermarkets in a city.
	Building-market POIs	Number of building materials markets in a city.
	Appliance-market POIs	Number of household appliances markets in a city.
	Integrated-market POIs	Number of integrated markets offering various products in a city.
	Agriculture-base POIs	Number of agricultural or farming bases in a city.
Freight facilities (2 features)	*Logistics-node POIs*	Number of logistical nodes or distribution centers in a city.
	Transport-hub POIs	Number of major transportation hubs in a city.
Road networks (3 features)	*Primary roads*	Total length of primary roads in a city (km).
	Secondary roads	Total length of secondary roads in a city (km).
	Motorway	Total length of motorway in a city (km).
Land uses (4 features)	*Retail landuse*	Total area of retail landuse in a city (km^2).
	Residential landuse	Total area of residential landuse in a city (km^2).
	Commercial landuse	Total area of commercial landuse in a city (km^2).
	Industrial landuse	Total area of industrial landuse in a city (km^2).
Demographic (1 feature)	*Population*	Total population counts in a city.

3.4. Model interpretation

Finally, SHapley Additive exPlanations (SHAP) is used to interpret the output of two XGBoost models to understand how city features contribute to the observed shifts in truck transport demand structures induced by COVID-19 pandemic. The interpretation results can help craft the responsive strategies for future crises and disruptions.

The foundational principle of SHAP draws inspiration from the Shapley values within cooperative game theory (Strumbelj and Kononenko, 2014). These values serve as a fundamental tool for quantifying the relative significance of individual features in a predictive model, offering insights into their interactions and collective influence on the model predictions. Specifically, a Shapley value greater than 0 signifies that the corresponding feature contributes positively to the model predictions. Conversely, a Shapley value less than or equal to 0 suggests that the inclusion of the corresponding feature has a neutral or negative impact on the model predictions. By calculating Shapley values, two different perspectives of interpretation can be provided. (1) Global feature importance: This aspect provides a holistic understanding of the contribution of each feature across the entire dataset. After calculating Shapley values for each feature, they are ranked based on their average impact on model predictions. This global interpretation helps identify which features consistently play a crucial role in influencing the model's outcomes, offering insights into the overall behavior of the predictive model. (2) Local feature importance: This aspect delves into the specific contribution of each feature to individual predictions, allowing for a nuanced interpretation at the level of individual city pair. By examining the Shapley values associated with each feature for distinct city pairs, the unique factors influencing the observed variations in truck transport demands can be pinpointed.

4. Results and analysis

The aggregated truck flows between all city pairs for each week before and after COVID-19 outbreak are obtained from large-scale truck GPS data. Next, the pandemic-induced changes in structure of intercity truck transport demand are quantified, focusing on two aspects, i.e., firstly the spatial trends of truck transport demand reduction (see **Section 4.1**) and secondly the patterns of demand reduction between cities (**Section 4.2**). Subsequently, the performance of two FTG models is evaluated (**Section 4.3**), and the shift in driving factors of intercity truck movements is uncovered (**Section 4.4**).

4.1. Spatial trends of truck transport demand reduction

The metric reduction ratio in total truck transport demand of each city is calculated by using aggregated truck flows before and after the COVID-19 outbreak, and the spatial autocorrelation analysis is employed based on this metric. The geographic distribution of demand reduction ratios of all cities in China is shown in **Fig. 2a**. The results of spatial autocorrelation analysis (see **Fig. 2c**) reveal a distinct spatial clustering pattern in the reduction of truck transport demand across cities. The results of LISA analysis in **Fig. 3a** suggest a positive correlation between the total demand reduction ratio of a city and the average value of this metric for its neighboring cities (i.e., spatial lag). This implies spatial clustering or autocorrelation, i.e., cities with higher reductions in transport demand tend to be surrounded by neighboring cities that also exhibit higher reductions in transport demand.

Specifically, the "high-high" values cluster around the vicinity of Wuhan, indicating that cities near Wuhan exhibit similarly high reduction ratios in truck transport demand. This suggests that the control measures, public health responses and economic impacts originating in Wuhan have a cascading effect on neighboring cities (Milani, 2021). The close correlation may be attributed to shared logistical dependencies, such as supply chain linkages and transportation networks, which were severely disrupted during the early stages of the pandemic (Singh et al., 2021). Conversely, the "low-low" values are distributed in the western remote areas, suggesting that these regions share a pattern of lower freight demand reduction. This spatial pattern suggests a distinct resilience or lesser vulnerability to the economic disruptions caused by the pandemic. These remote areas are less densely populated or less economically integrated, potentially leading to a more gradual impact on their freight transport systems.

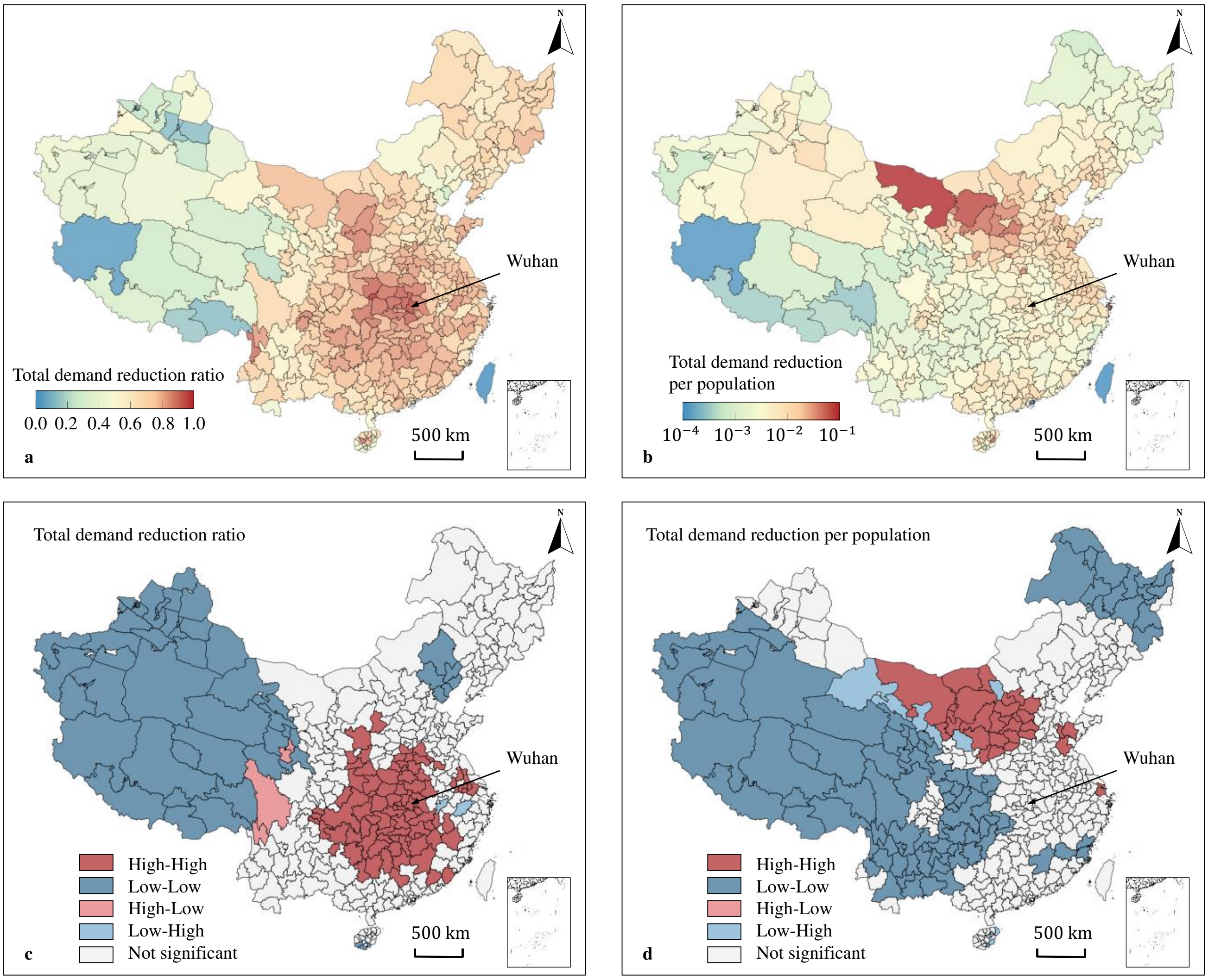

Fig. 2. Spatial autocorrelation analysis of truck transport demand reduction. **a** Distribution of total demand reduction ratio of all cities in China. **b** Distribution of total demand reduction per population. **c-d** The results of spatial autocorrelation analysis for these two metrics.

To understand the localized effects and variations related to city population size, the ratio of total truck transport demand reduction to population of each city is further calculated (see **Fig. 2b**), and spatial autocorrelation analysis is conducted based on this metric (see **Fig. 2d**). The results of LISA Analysis (see **Fig. 3**) indicate a significant difference for the distribution of "high-high" values and "low-low" values across the country. Specifically, the cities with "high-high" values are no longer clustered around the vicinity of Wuhan as observed previously when the overall reduction in truck transport demand is normalized by city population. In contrast, some of these cities even exhibit 'low-low' values. Cities vary in their economic structures, with some being more industrialized, while others are service-oriented or agricultural (Henderson, 2010). Cities near Wuhan might have diverse economic structures and dependencies (Gao et al., 2020). When normalized by population, variations in economic activities and dependencies on freight transport may become more apparent. This new metric captures the impact of COVID-19 on different sectors, leading to varied patterns across cities. This diversity may result in the dispersion of "high-high" values, reflecting localized economic characteristics rather than geographic proximity to Wuhan. Conversely, the continued distribution of "low-low" values in the western remote areas in this updated metric implies that these regions still share a pattern of lower freight demand reduction relative to their population sizes. This consistency underscores the limited vulnerability of these remote areas to the economic disruptions caused by the pandemic.

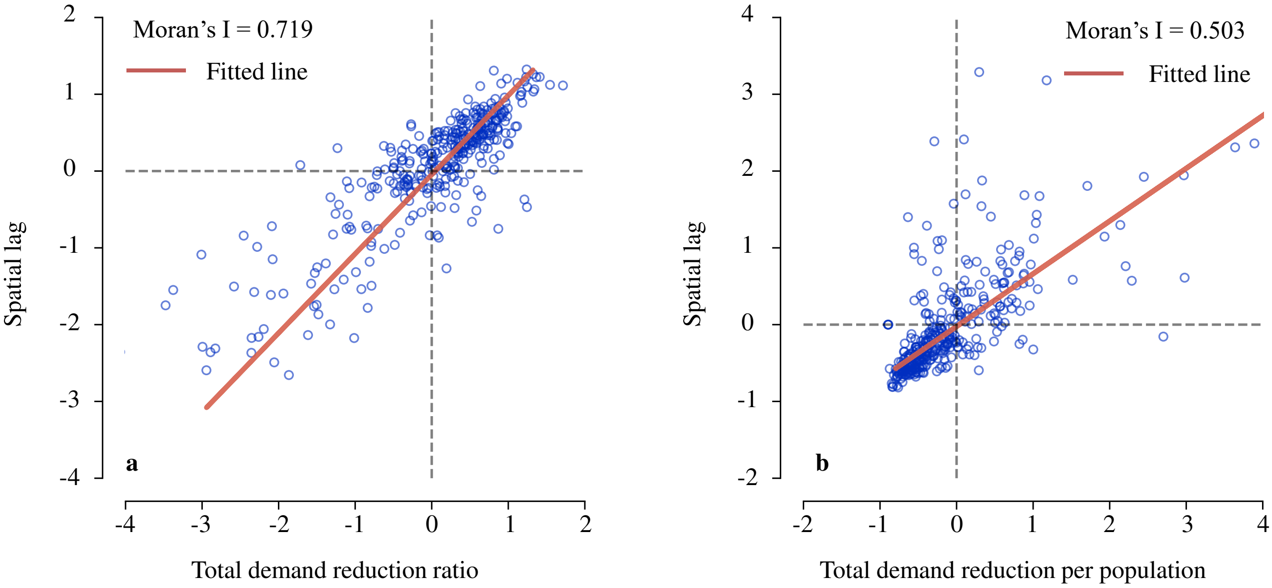

Fig. 3. Results of local indicators of spatial association (LISA) Analysis. **a** Moran scatterplot for total demand reduction ratio of all cities in China. Each point represents a city, with the horizontal axis representing z-standardized attribute value and the vertical axis representing z-standardized spatial lag value for this city. The spatial lag values are calculated by taking a weighted average of the attribute values (i.e., the total demand reduction ratio) of neighboring cities. The line represents the fitted positive correlation. **b** Moran scatterplot for total demand reduction per population of all cities in China.

4.2. Truck transport demand reduction patterns between cities

Next, bidirectional total truck transport demands between all city pairs before and after COVID-19 outbreak are calculated respectively, and demand reduction of each city pair can be derived. **Figure 4a-b** shows the distributions of truck transport demands between all city pairs nationwide before and after COVID-19 outbreak. The results suggest that the overall truck transport demands across nation experienced a sharp decline, underscoring the widespread impact of the COVID-19 pandemic on the logistics and transportation sectors. Particularly for the freight interactions between Wuhan and other cities (as shown in **Fig. 4c-d**), following the onset of the COVID-19 pandemic and the subsequent lockdown in Wuhan, truck transport demands between this city and its counterparts have undergone significant changes.

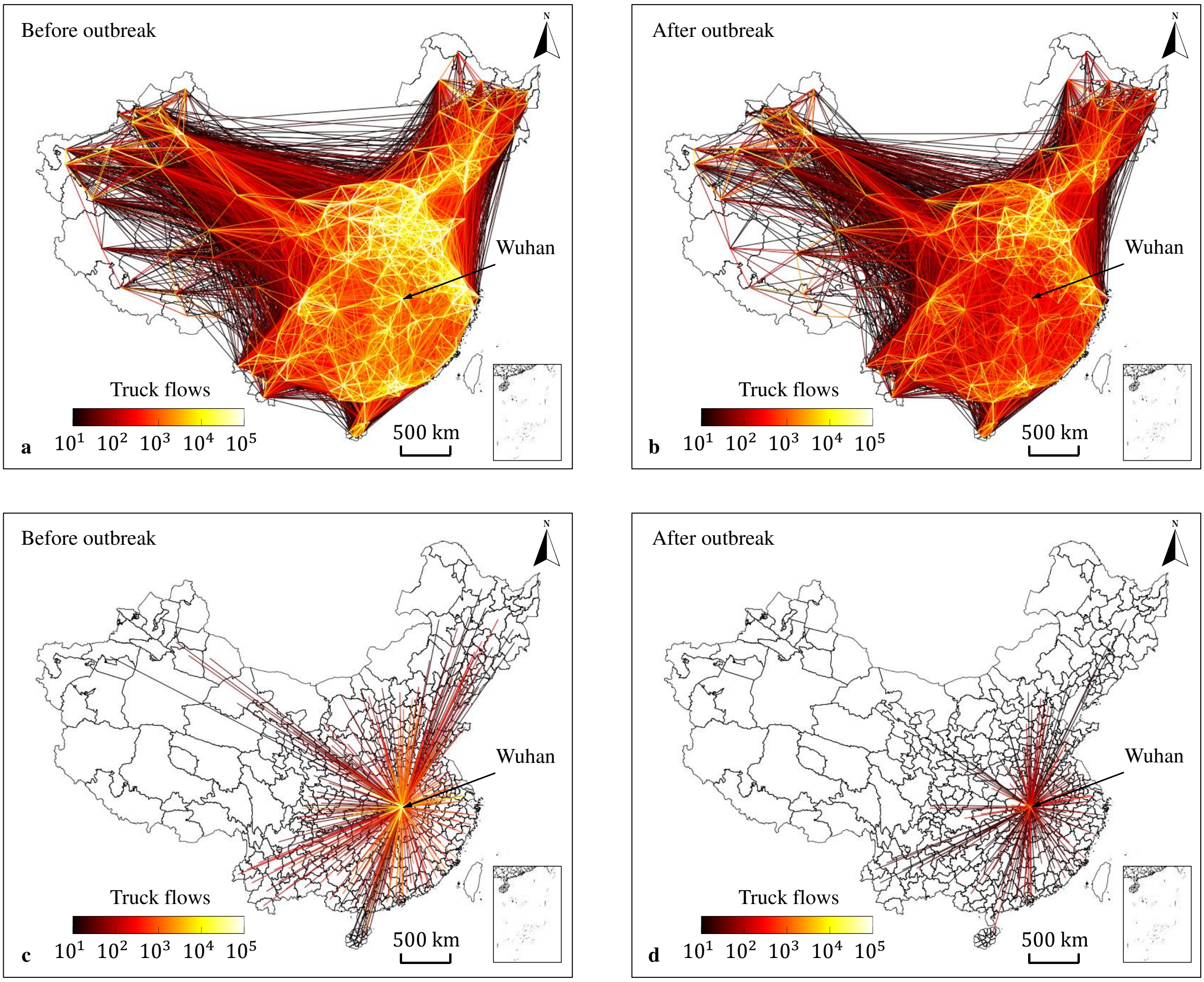

Fig. 4. Spatial distributions of intercity truck transport demands before and after COVID-19 outbreak. **a-b** Distributions of transport demands between all city pairs. Each line represents the interaction between two cities. The color of the line indicates the number of freight trips, indicated as truck flows, between those two cities. **c-d** Distributions of transport demands between Wuhan and other cities.

To further uncover demand reduction patterns between cities, four typical cities, i.e., Wuhan, Beijing, Shanghai, and Guangzhou, are selected for case analysis. For each case city, the reduction in transport demands between it and other interacting cities and their spatial distances are calculated. The top 50 interacting cities with the most significant demand reduction are shown in **Fig. 5**. The results suggest a trend where interacting cities closer in proximity to the case cities tend to exhibit a larger demand reduction. Shorter spatial distances generally imply more interconnected networks. Cities located closely to each other often share common transport routes and dependencies (Rodrigue, 2020). The disruptions in one city can quickly propagate to neighboring cities, impacting the overall transport demands. In addition, geographically proximate cities often share economic interdependencies. Industries and businesses in nearby cities might be more dependent on each other for raw materials, goods, and services (Lv et al., 2024; Pinch and Sunley, 2016). Therefore, economic downturns and disruptions in one city would have a more immediate and profound effect on nearby cities.

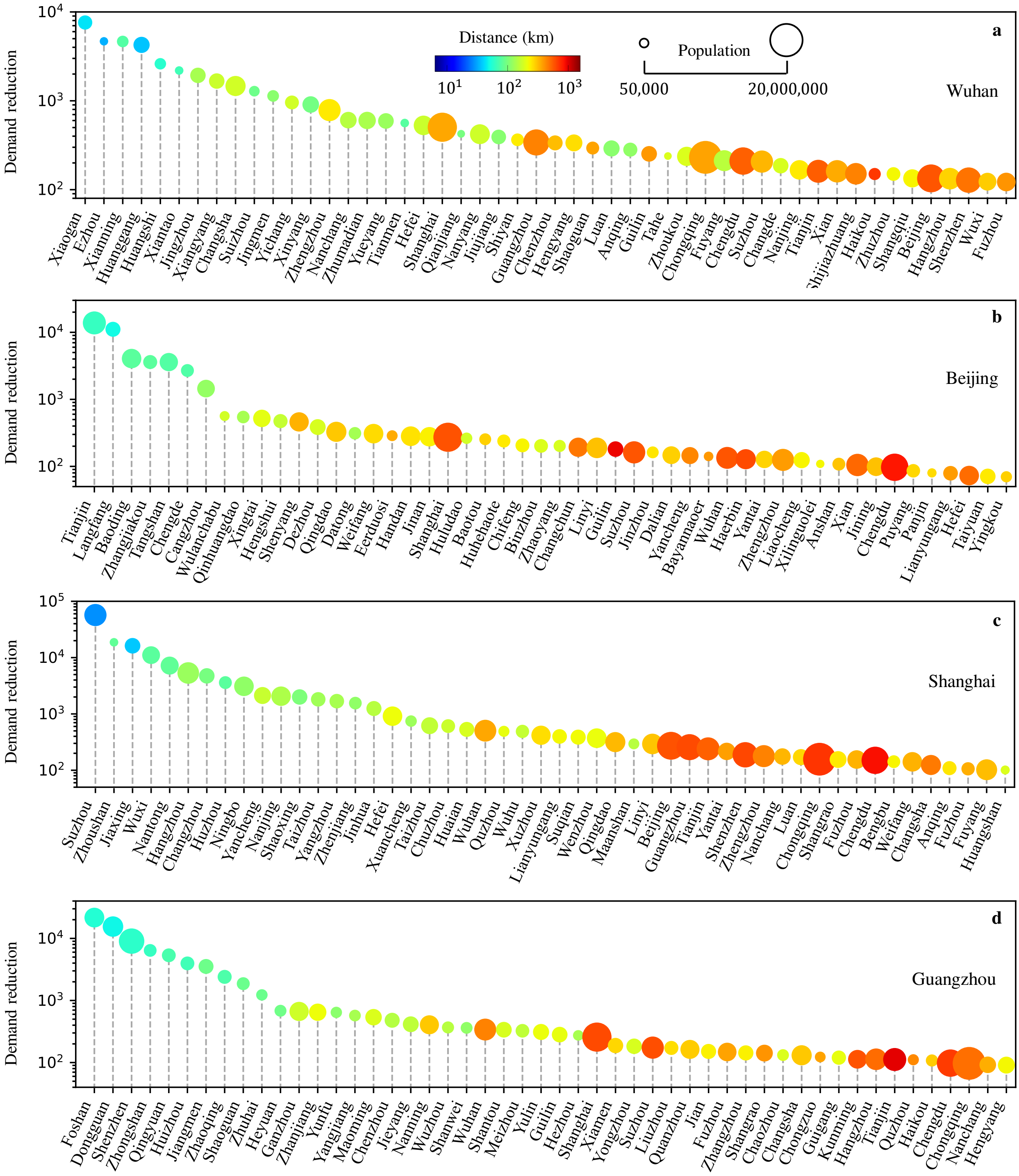

Fig. 5. Truck flows reduction between four case cities, i.e., Wuhan (panel **a**), Beijing (panel **b**), Shanghai (panel **c**), and Guangzhou (panel **d**), and other interaction cities due to COVID-19 outbreak. For each case city, we select the top 50 interaction cities with the greatest reduction in truck flows between them, as listed on the horizontal axis. The size of the circle represents the population of an interaction city, and the color of circle indicates the spatial distance between the case city and an interaction city.

In addition to the observed spatial effects in neighboring cities, numerous distant cities with substantial populations also encountered noteworthy demand reductions, as illustrated in **Fig. 5**. To understand this pattern related to both the distance and city population, this study examines the distribution of demand reduction

$T_{ij}^{reduction}$ between each city pair i and j, along with the term $POP_i \cdot POP_j / d_{ij}$, in which POP_i denotes the population size of city i, and d_{ij} denotes distance between city i and j. The results suggest the scaling relationship between these two metrics, as shown in **Fig. 6**. This scaling relationship is also known as gravitational relationship (Jung et al., 2008; Krings et al., 2009), indicating that transport demand reduction between two cities is positively associated with their populations and inversely related to the distance separating them. Larger cities often serve as distribution, manufacturing, or economic hubs with more extensive and diverse economic activities. Disruptions in these key cities can have a cascading effect on the entire supply chain, affecting cities across distances (Shughrue et al., 2020). The observed gravitational relationship reflects the complex interplay of economic, demographic, and geographical factors that influence the dynamics of intercity transport demands.

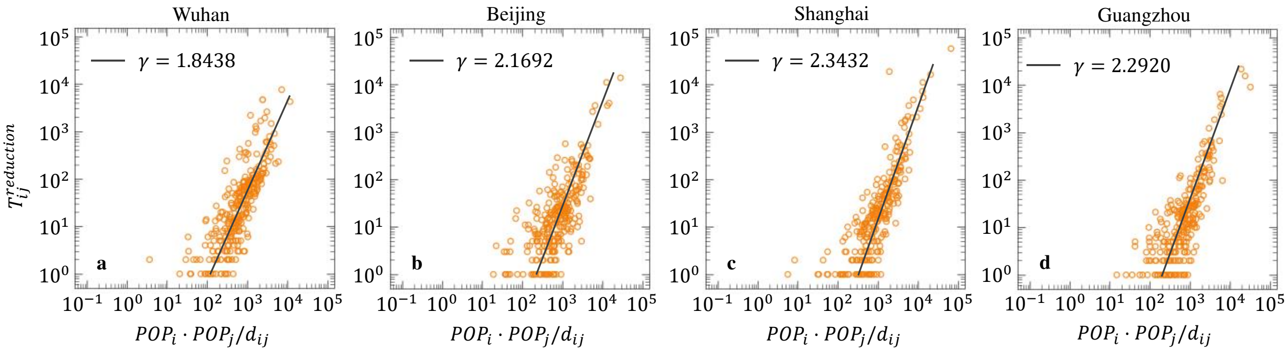

Fig. 6. Distributions of intercity transport demand reduction with respect to spatial distance and city population. The data are distributed on the double-logarithmic axes. The hollow point represents city pair, and the line represents the fitted scaling relations between two terms with the fitted exponent γ.

4.3. Performance of intercity FTG model

The above sections quantify the changes in structure of intercity truck transport demand. In this section, the XGBoost model is constructed and trained based on real data to predict such pandemic-induced shifts. By using the input samples and two created labels, i.e., total transport demands between all city pairs before (label 1) and after (label 2) COVID-19 outbreak, two XGBoost models are trained respectively. The first one is used to predict the intercity truck transport demands before COVID-19 outbreak, and the second one is used to predict those after COVID-19 outbreak. The results of the comparison between real transport demands and the transport demands generated by two XGBoost models are shown in **Fig. 7**. The results demonstrate that the model can effectively capture the intricate relationships between various city features and intercity truck movements both before and after the COVID-19 outbreak. This underscores the effectiveness of model in predicting the dynamic shifts in truck transport demands induced by the pandemic.

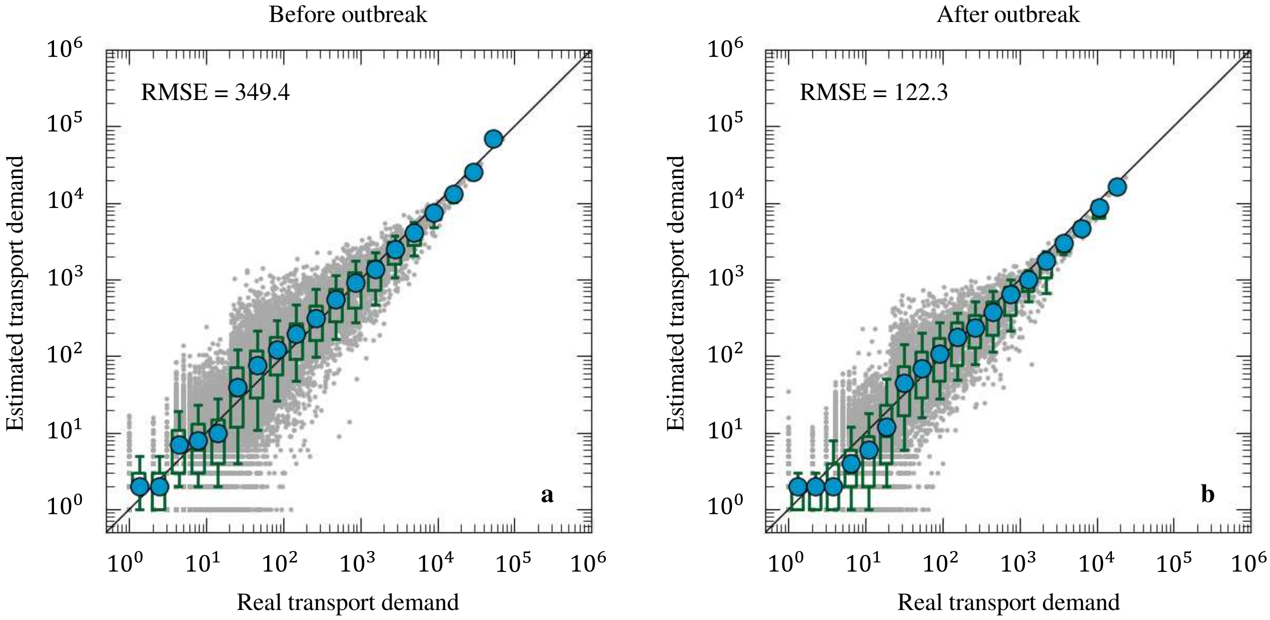

Fig. 7. Model performance evaluation. Distributions of the transport demands generated by the model and the real transport demands before and after COVID-19 outbreak are shown in panels **a** and **b** respectively. The grey points are scatter plot for city pairs. The blue points represent the predicted average transport demands in different bins. The boxplots represent the distribution of the predicted demands in different bins of the real demands. A box is marked in blue if the line y=x lies between 10% and 91% in that bin.

4.4. Shift in driving factors of intercity truck movements

In this section, SHAP technique is used to explain the outputs of two XGBoost models respectively, aiming to uncover the driving factors of intercity truck movements before and after COVID-19 outbreak. Next, the pandemic-induced shift in the driving factors is analyzed to understand how the landscape of truck logistics has evolved in response to the challenges posed by the COVID-19 pandemic.

First, the global Shapley values of each feature across the entire dataset are calculated, and they are ranked based on their average impact on model predictions. The results of global feature importance analysis for two models are shown in **Fig. 8**. The findings indicate a substantial disparity in the driving factors of truck movements due to the outbreak of COVID-19 pandemic. Before the pandemic, as illustrated in **Fig. 8a**, the analysis reveals that features such as machinery POIs, population, and logistics-node POIs in destination cities had a pronounced influence on intercity truck movements. Specifically, higher values of these features correlated with higher Shapley values, indicating their importance in predicting truck movement patterns. In addition, original cities with higher concentrations of factory POIs and larger industrial land use areas typically exhibited higher Shapley values, indicating that these features also played significant roles in facilitating truck movements. These findings align with the emphasis on manufacturing and logistical considerations in the pre-COVID-19 era (Ozkanlisoy, 2021).

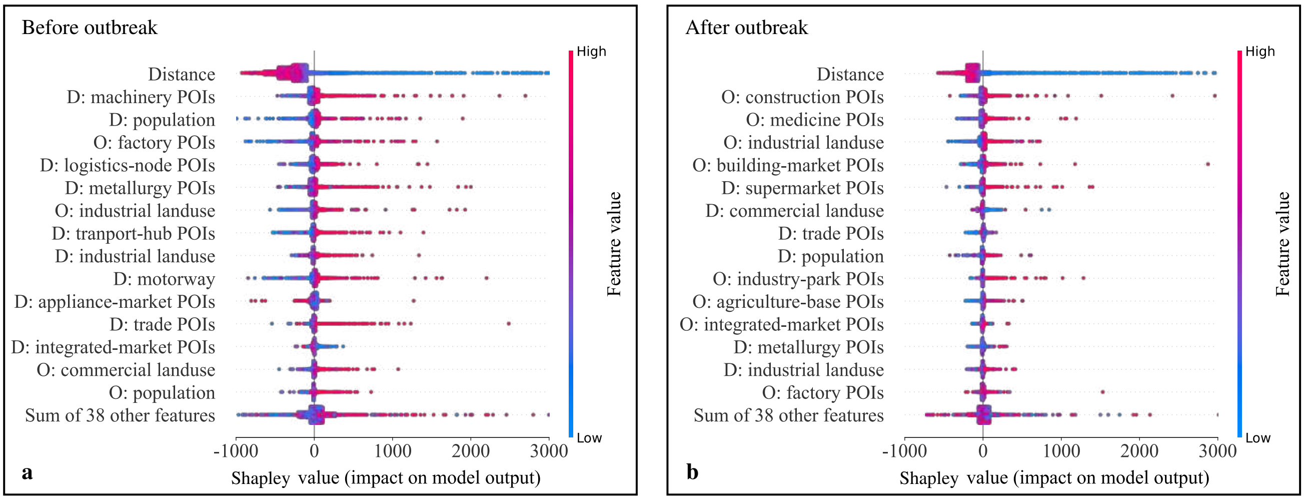

Fig. 8. Analysis of global feature importance for the output of XGBoost model. **a** Results before the COVID-19 outbreak. **b** Results after the COVID-19 outbreak. The features are represented on the vertical axis, organized in descending order of significance from the most impactful at the top to the least impactful at the bottom. The significance of a feature is characterized by the average absolute Shapley values of this feature for all city pairs. Features prefixed with "O:" and "D:" correspond to origin and destination city features respectively. Each point represents a city pair, with the colorbar indicating the feature values associated with each city pair. The horizontal axis represents the Shapley value of the feature for the given city pair, providing a quantitative measure of its impact.

In contrast, **Fig. 8b** depicts the altered landscape after the COVID-19 outbreak. Notably, supermarket POIs in the destination city have gained significant prominence. Higher values of supermarket POIs correlate with elevated Shapley values, indicating their heightened importance in predicting post-pandemic truck movement patterns. The surge in demand for essential goods prompted a reconfiguration of logistics strategies to accommodate the evolving needs of the population (Thilmany et al., 2021). Simultaneously, features such as construction POIs, medicine POIs, and industrial land use in the origin city have also become more influential in facilitating truck movements after the COVID-19 outbreak. These shifts suggest adaptations in supply chains and economic activities, where construction activities, medical supply chains, and industrial production have gained prominence in driving intercity truck movements. The increased Shapley values associated with these features underscore their critical roles in the new logistics landscape shaped by the pandemic (Garola et al., 2023).

Second, the local Shapley values associated with each feature for distinct city pairs are calculated, aiming to pinpoint city-specific driving factors that may not be evident in the global analysis. A short-distance city pair (i.e., from Xiaogan to Wuhan) and a long-distance city pair (i.e., from Shanghai to Wuhan) are selected. The results of local feature importance analysis for these two city pairs are shown in **Fig. 9**. For the short-distance city pair before COVID-19 outbreak (see **Fig. 9a**), features like distances, number of factors in destination city (Wuhan), number of integrated markets in origin city (Xiaogan) significantly promote truck movements. It is important to note that while distance is typically a negative factor in freight movements, in the context of short-distance city pairs, it can be a positive factor that facilitates more efficient truck mobility compared to other longer-distance samples in the SHAP method. Conversely, the number of trade points in origin city acted as a hindrance, possibly due to logistical complexities or congestion associated with trade points, making the movement less efficient. After the lockdown in Wuhan, a shift in the factors influencing truck movements can be observed (see **Fig. 9b**). Specifically, two features of industrial land area and the length of primary roads in Wuhan exhibit a negative impact on truck mobility, indicating potential challenges or disruptions in the industrial and transportation infrastructure (Wan et al., 2018). Factors such as reduced workforce, altered traffic patterns, or regulatory changes might have contributed to this negative influence. Conversely, the quantity of integrated markets and supermarkets in Wuhan emerged as positive influencers on truck movements during this period. The positive impact suggests these retail and distribution centers played a key role in supporting the resumption of economic activities and the movement of goods within the city.

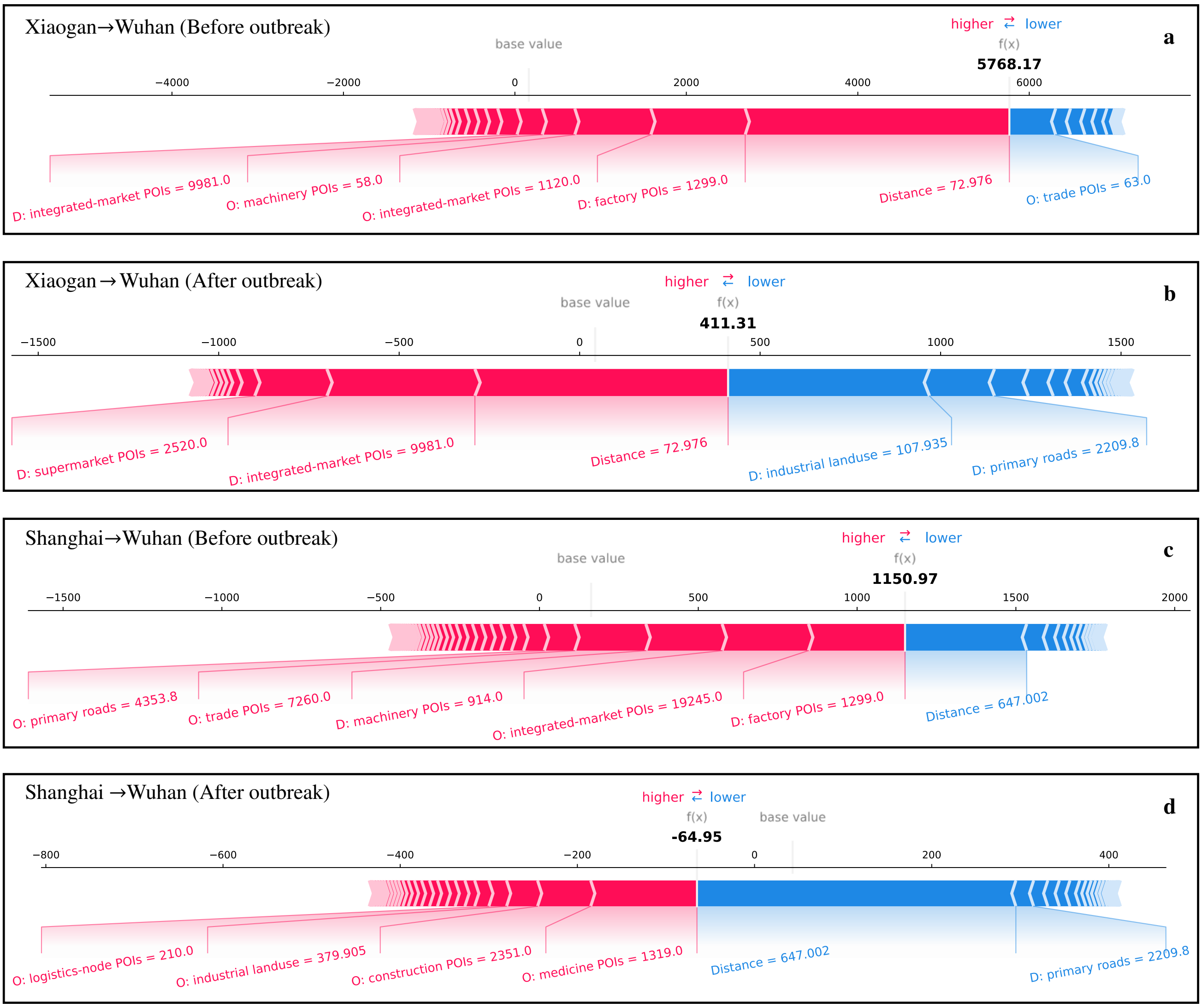

Fig. 9. Force plot of local feature importance analysis. **a-b** Results for short-distance city pair from Xiaogan to Wuhan before and after COVID-19 outbreak. **c-d** Results for long-distance city pair from Shanghai to Wuhan before and after COVID-19 outbreak. Each horizontal bar corresponds to a feature in the model, and its length represents the local Shapley value of that feature for the specific instance. Longer bars indicate a higher positive or negative impact on the prediction. Positive Shapley values are depicted in red, while negative Shapley values are in blue. The features and their values are at the bottom of the figure.

For the long-distance city pair from Shanghai to Wuhan (see **Fig.9c-d**), the results indicate that the high number of companies related to medicine and construction in Shanghai exhibit a significant positive impact on truck mobility after the lockdown of Wuhan. There emerges an increased demand for medical supplies and pharmaceuticals in Wuhan, prompting a surge in truck movements from Shanghai to fulfill these needs. Additionally, the positive influence of construction-related companies indicates a demand for materials and services essential for post-outbreak construction efforts, including the reconstruction of healthcare facilities and other critical infrastructure projects in Wuhan. The observed truck mobility patterns underscore the interconnectedness of industries and the adaptability of logistics systems in responding to the complex challenges posed by the lockdown (Bandyopadhyay and Bhatnagar, 2023). The collaboration between diverse industries in Shanghai contributes to the effective restoration of infrastructure and healthcare capabilities in Wuhan, emphasizing the role of diverse industries in fostering recovery and resilience in the face of unprecedented events.

5. Discussion

This study contributes insights to the understanding of intercity FTG dynamics during the pandemic by combining a novel dataset, quantitative analyses and an interpretable machine learning framework. The findings highlight that the demand for inter-city freight transport was reduced in a gravitational pattern, meaning that the impact was more pronounced in cities with higher economic activities and population densities. This observation aligns with the principle of gravitation in transport geography (Hesse and Rodrigue, 2004), where larger and more economically active cities exert a greater influence on freight movements. However, during the pandemic, these cities also faced stricter lockdown measures and higher disruption levels, leading to more significant reductions in freight transport demand. This finding underscores the importance of considering city size and economic activity levels in intercity freight planning during crises.

Using the SHAP technique to explain the outputs of developed XGBoost-based FTG model, significant changes in the factors influencing intercity freight movements after the COVID-19 outbreak were identified. This analysis extends the findings of prior studies (de Oliveira et al., 2022; Holguin-Veras et al., 2011; Jesus et al., 2020; Middela and Ramadurai, 2024) by providing a more detailed understanding of how specific sectors influenced freight movements during the pandemic. For instance, one of the most notable changes observed was the increased prominence of supermarkets in cities. As a city implemented lockdown measures, residents relied more on local supermarkets for their daily necessities, which were supplied from other cities. Supermarkets became crucial nodes in the logistics network and attracted a substantial volume of truck movements from other cities. Moreover, the findings indicated the growing influence of medical and construction locations in cities after pandemic outbreak. Cities with surplus resources in these sectors would transport excess supplies to other cities, leading to a significant increase in generated truck trips.

Additionally, prior study (Yang et al., 2023a) has indicated that factors influencing intercity freight transport can vary significantly between different city pairs. This study contributes to the literature by demonstrating that pandemic exacerbated this difference. This study found that short-distance city pairs, such as Xiaogan to Wuhan, saw increased freight movements driven by local demand surges, particularly for essential goods, while long-distance pairs, such as Shanghai to Wuhan, experienced more substantial disruptions due to logistical challenges and stricter lockdown measures. The finding highlights the need for differentiated strategies in managing intercity freight transport based on the specific context and distance between city pairs.

Furthermore, SHAP analysis can offer implications for understanding and modeling intercity freight transport demand, especially in the context of the COVID-19 pandemic. Traditionally, FTG models have relied on established patterns of economic activity and population density to estimate freight movements between regions. However, the pandemic has reshaped these patterns, necessitating a reevaluation of how industries and sectors contribute to FTG. For instance, before the pandemic, manufacturing industries typically dominated FTG due to their substantial production volumes and distribution networks (Holguin-Veras et al., 2011). In contrast, during the pandemic, sectors such as healthcare and construction gained prominence amid evolving demands. Different industries dominate FTG, but their own FTG rates could be different before and during pandemic. The SHAP analysis in this study revealed potential variability in FTG rates across industries, which could be incorporated into FTG models, such as the trip rate model (Jesus et al., 2020), to improve their responsiveness to crisis situations.

Finally, compared to traditional trip rate models that rely on simplistic assumptions about sectoral contributions to freight movements, the developed XGBoost-based FTG model in this study offers greater flexibility and adaptability. The XGBoost model's capability to handle large datasets allows it to effectively integrate diverse sources of information, including real-time economic indicators, transportation network conditions, and sector-specific demands. This approach enables more accurate predictions of freight flows even under unprecedented circumstances like the COVID-19 pandemic, where conventional assumptions about economic activities and transport patterns may no longer hold true. This model can be provided as a tool to predict freight demand between cities for future crises and disruptions. Initially, the model requires the integration of up-to-date and relevant data, encompassing economic indicators, population statistics, infrastructure details, and industry-specific variables. Next. robust validation methods (Yadav and Shukla, 2016) are needed to be implemented to ensure the accuracy and reliability of incoming data. By simulating various potential crises or disruptions, scenario-based predictions can be generated by the model, providing supports for freight management practices (Cleophas et al., 2019; Nocera et al., 2021; Tavasszy et al., 2012).

6. Conclusion

This study leveraged a novel dataset to capture large-scale truck movements during the COVID-19 pandemic, offering a detailed analysis of intercity transport systems. The structural changes in intercity truck transport demand were quantified, providing insights into the freight dynamics under the COVID-19 outbreak. Additionally, an interpretable machine learning framework was introduced for precise intercity freight demand estimation. The findings reveal the intricate interplay of factors influencing intercity truck transport systems during the COVID-19 crisis and offer potential implications to enhance the resilience of freight transport systems. This research contributes valuable insights for optimizing freight logistics and building a more adaptable transportation infrastructure in the post-pandemic era.

Despite the comprehensive analysis of the impact of the COVID-19 pandemic on intercity truck movements, this study has several limitations and provides a promising research agenda for the future. First, this study utilized truck movement data for one week before and after the pandemic outbreak to capture the short-term changes brought about by the COVID-19 outbreak. It does not provide insights into the medium and long-term changes in freight demand after the implementation of various policies. Future research could delve into the temporal dynamics of intercity truck transport, examining how the patterns observed during the immediate aftermath of the COVID-19 outbreak evolve over time. Long-term trends may reveal sustained changes in freight demand, adaptive strategies employed by the industry, and the resilience of supply chains in the post-pandemic era. Second, the study overlooks the changes in the distribution of freight POIs resulting from the policies before and after the pandemic. For example, the closure of certain factory facilities following the occurrence of COVID-19. Future research could explore these critical aspects by integrating geospatial analysis with real-time data on freight movements. By tracking the shifting patterns of freight POIs in response to pandemic-related policies, such as factory closures, researchers can gain a nuanced understanding of how supply chain dynamics evolve under stress. Third, this study selected two short-distance and long-distance city pairs to capture the diversity and complexity of driving factors influencing freight flows across varying distances. The two selected samples may not be representative for all distances and regions. Future research could broaden this scope by including a more diverse range of city pairs. By encompassing cities with varying economic structures, transportation infrastructures, and regional characteristics, researchers can better generalize findings across different urban contexts and identify commonalities and disparities in intercity freight dynamics.

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