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Estimating intercity heavy truck mobility flows using the deep gravity framework

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A R T I C L E I N F O

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A B S T R A C T

Accurate estimation of intercity heavy truck mobility flows is of vital importance to urban planning, transportation management and logistics operations. The inaccessibility of big data related to intercity transport systems and the heterogeneity of trucking activities pose challenges for the reliable estimation. Recently, the advance of Artificial Intelligence (AI) provides a potential solution to this problem. However, most previous studies focused on the estimation of inter-regional passenger mobility. In-depth studies of estimating intercity heavy truck mobility flows by using deep learning techniques are still scarce. To fill in the gaps, we construct a deep neural network based on the Deep Gravity framework, an advanced predictive model for human mobility. We collect a wide range of data related to heavy truck movements, freight locations, road networks and land uses to train the model, and validate its high performance by comparing to traditional gravity model. Furthermore, we use an explainable AI technique to interpret how the city features contribute to the determination of intercity heavy truck movements, and the results can provide valuable policy implications for logistics operations, businesses and urban planning.

1. Introduction

Intercity freight transport system plays a vital role in the functioning of modern economies and societies. It enables the efficient movement of goods between cities, driving economic growth and supporting global trade (Liu et al., 2017; Yang et al., 2022b). Heavy trucks are the primary vehicles used for intercity road freight transportation. They are typically designed to carry large volumes of cargo over long distances, facilitating the movement of materials that are essential for various industries and supporting intercity logistics operations (Malik et al., 2019; Ozdagoglu et al., 2022; Trigell et al., 2017; Yang et al., 2022a). Heavy truck flows are crucial for the functioning of supply chains, as trucks transport various commodities such as raw materials, manufactured goods and consumer products across regions. Accurate estimation and prediction of heavy truck mobility flows between cities allow transportation

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planners, policymakers, and businesses to understand and plan for future transportation needs. By harnessing this information, stakeholders can make informed decisions regarding infrastructure development, resource allocation, urban economic planning, traffic management, and strategic policy development (Demissie and Kattan, 2022; Kinjarapu et al., 2022; Siripirote et al., 2020).

Estimating intercity heavy truck mobility flows, also known as trip distribution or origin–destination (OD) synthesis (Demissie and Kattan, 2022; Zanjani et al., 2015), aims to estimate the number of freight trips between different city pairs, and the results are typically presented in an OD matrix. This can be a complex task, as it involves understanding and modeling numerous factors that influence the movement of goods and services between cities. The first challenge is that accurate and detailed data on freight movements and infrastructure can be difficult to obtain (Malik et al., 2021; Siripirote et al., 2020), and this hinders reliable estimations. The second challenge is the heterogeneity of trucking activities. Trucking activities vary significantly by geography, industry sector, distance and regulations (Cantillo et al., 2022; Dadsena et al., 2019). The diversity inherent in this situation poses challenges in developing a practical model for estimating intercity heavy truck mobility flows.

To address these challenges, researchers and transportation planners have developed various methods and models. One of the most common classes of models is the spatial interaction models (e.g., gravity model) (Boukebbab and Boulahlib, 2015; Dhulipala and Patil; Simini et al., 2012; Tamin and Willumsen, 1990; Venkadavarahan and Marisamynathan, 2021; Yan et al., 2017b), which use mathematical equations to estimate the truck or cargo flows between different regions, taking into account factors such as distance and economic activity. Spatial interaction models are easy to interpret and can be used to make estimations even when data are missing or incomplete, and therefore widely applied in practice. However, these models rely on a limited set of variables, i.e., distance and economic activity, to estimate mobility flows. Their inability to account for other important factors, such as road network connectivity, land use patterns and industry sectors, can limit their accuracy and usefulness (Pamula and Zochowska, 2023). In the era of big data, Artificial Intelligence (AI) is becoming the new foundation of business operations and logistics (Bian et al., 2021; Hassan et al., 2020; Leung et al., 2018; Luo and Choi, 2022; Ma et al., 2021; Oluleye et al., 2023; Ren et al., 2020; Yan et al., 2022; Yu et al., 2022), providing a potential solution to this problem. Most previous studies (Jiang and Luo, 2022b; Kong et al., 2023; Luca et al., 2023; Shuai et al., 2022; Yao et al., 2021) focused on the estimation of passenger mobility by using machine learning methods. Specifically, the Deep Gravity model proposed by Simini et al. (2021) shows its high performance in predicting interregional human mobility flows by integrating rich geographical factors. However, in-depth studies of estimating intercity heavy truck mobility flows by using deep learning models are still scarce, because the inaccessibility of big data related to intercity transport systems.

This paper aims to estimate and interpret intercity heavy truck mobility flows by using AI techniques, and to provide practical implications for logistics operations and urban planning. In the paper, we have obtained massive intercity mobility data of 2.7 million heavy trucks in China, and national-scale freight point-of-interest (POI) data and geographic data. By using these data, we collect a wide range of city features related to freight companies, markets, facilities, road networks, land uses and freight demands. To estimate intercity heavy truck mobility flows, we utilize the Deep Gravity framework to construct an artificial neural network. The performance of the Deep Gravity model is validated by comparing its results with the predictions of the traditional singly constrained gravity model. Furthermore, we use explainable AI techniques to interpret the output of Deep Gravity model, aiming to uncover the factors contributing to intercity heavy truck movements, heterogeneity of influencing factors across city pairs, and synergistic and antagonistic effects related to space. Finally, we analyze the potential applications of Deep Gravity model in practice, and provide policy implications for logistics operations and urban planning inspired by the interpretation results of the model.

Our study contributes to the literature are four folds. First, we enhance the Deep Gravity model by incorporating new features relevant to urban freight transportation, improving predictive accuracy for heavy truck mobility flows between cities. Second, we reveal the factors contributing to intercity heavy truck movements, supporting policy making for urban freight economy development. Third, we uncover the heterogeneity of influencing factors across city pairs, supporting the development of tailored logistics policies and flexible regulatory frameworks. Fourth, we discover the synergistic and antagonistic effects related to space, supporting the development of efficient long-haul intercity transport system.

The remainder of this paper is organized as follows: **Section 2** gives the literature review. The collection and details of big data related to intercity transport systems are presented in **Section 3**, and the methods of the construction of Deep Gravity model, performance evaluation and interpretation are provided in **Section 4**. We describe the model estimation results and how the city features contribute to the determination of intercity heavy truck movements in **Section 5**, discuss the potential applications and policy implications of Deep Gravity model in **Section 6**. Finally, **Section 7** at the end, offers concluding insights.

2. Literature review

Our work is related to two streams of the literature: the first estimate mobility flows using spatial interaction models, and the second traffic estimation using machine learning methods.

2.1. Estimating mobility flows using spatial interaction models

Over the past several decades, spatial interaction models have emerged as essential tools for estimating the movement of people, goods or information between various regions. spatial interaction models belong to a class of mathematical models that elucidate the relationships and interactions between spatially distributed entities, such as individuals or commodities, across geographical space. The basic principle underlying spatial interaction models is that the interaction between two locations is influenced by both the characteristics of the locations themselves and the distance or impedance between them. Gravity models are the foundation of spatial interaction models, and their origins can be traced back to the works of Stewart (1941) and Zipf (1946). These models assume that the interaction between two locations is proportional to their masses (e.g., population size) and inversely proportional to the distance between them. Wilson (1967) further refined gravity models by incorporating entropy-maximizing principles, which have been widely adopted in the literature (Fotheringham and O'Kelly, 1989; Haynes and Fotheringham, 1985). Gravity models are easy to understand and interpret, therefore have a wide range of practical applications in freight mobility flows estimation (Arbues and Banos, 2016; Duanmu et al., 2012; Gentile and Vigo, 2013; Havenga and Simpson, 2018; Kalahasthi et al., 2022; Levine et al., 2009; Metaxatos, 2009; Middela et al., 2018; Prentice et al., 1998; Shen and Aydin, 2014; van den Heuvel et al., 2014). Besides the gravity model, previous studies have proposed many other spatial interaction models, including radiation model (Simini et al., 2012), population-weighted opportunities model (Yan et al., 2014), universal opportunity model (Yan et al., 2017a) and opportunity priority selection model (Liu and Yan, 2019).

In summary, spatial interaction models are essential tools in understanding and managing transport systems, informing policy decisions related to transportation infrastructure and services. However, these models also have significant limitations in estimating intercity heavy truck mobility flows. They often rely on over-simplified assumptions about the factors, such as distance, economic activity at origin and destination cities, influencing intercity heavy truck flows. However, they may overlook other significant factors like network connectivity, land use patterns and industry sectors, leading to inaccurate estimates. In addition, spatial interaction models often assume linear relationships between variables, which can limit their ability to capture non-linear and complex relationships present in real-world truck flows, lacking a reasonable explanation for the predicted truck flows.

2.2. Traffic forecasting by machine learning techniques

Since the early 1990s, machine learning techniques have been increasingly utilized in transportation research, particularly in travel demand modeling (Celik, 2004). Machine learning techniques are regarded as a viable alternative to traditional models for traffic forecasting, due to their remarkable ability to capture nonlinearities and exhibit robustness against diverse distributional properties of data. For this reason, machine learning techniques are commonly perceived as a compelling approach for policy and planning analysis (Golshani et al., 2018).

Machine learning algorithms, such as artificial neural networks (ANNs) (McCulloch and Pitts, 1990) and support vector machines (Cortes and Vapnik, 1995), can be trained on historical travel demand data to predict the origin–destination matrix (Tang et al., 2021). The input features for these models can include travel time, distance, mode of transportation and other relevant variables that influence the demand for travel between different origin–destination pairs. Machine learning algorithms have the capability to incorporate information pertaining to external factors, including weather conditions, traffic incidents and public events, which can have an impact on travel demand. By leveraging historical data, these models can discern the patterns and trends in travel demand, enabling accurate estimation of the OD matrix. Recently, a great deal of studies (Afandizadeh Zargari et al., 2021; Chu et al., 2020; Feng et al., 2022; Goedel et al., 2022; Jiang et al., 2022; Li et al., 2020; Liu et al., 2023; Ma et al., 2020; Noursalehi et al., 2022; Rodriguez-Rueda et al., 2021; Rong et al., 2023; Sana et al., 2018; Tang et al., 2021; Ul Abideen et al., 2022; Yan et al., 2019) has been done on methods for estimating traffic volume or estimating the OD matrix using machine learning techniques. Due to the advances in hardware and algorithms, and the growing demand across industries, deep learning and reinforcement learning techniques have also been developed and applied to traffic forecasting, as summarized in the review articles (George and Santra, 2020; Jiang and Luo, 2022a; Tedjopurnomo et al., 2022; Yin et al., 2022). These methods greatly increase the possibilities of traffic estimation.

In summary, these previous deep learning models like RNNs, CNNs or GNNs offer advantages such as capturing temporal dependencies, incorporating spatial patterns or modeling complex network structures. However, they may lack the interpretability or simplicity for predicting freight mobility flows. These models learn complex patterns and relationships from the data without relying on explicit assumptions or freight domain knowledge, making it difficult to interpret the learned representations and understand the underlying drivers of freight mobility flows. In addition, these models often have complex architectures with multiple layers and parameters, and require massive training data. Due to the model complexity, in-depth studies on estimating intercity freight mobility flows by deep learning techniques are still lacking, because of the difficulty in obtaining big data related to intercity transport systems. Moreover, the drivers of intercity heavy truck movements also need to be further explored by studying explainable AI techniques.

3. Data

In the paper, we use three datasets, i.e., heavy truck GPS data, freight point-of-interest (POI) data and geographic data, to capture the intercity heavy truck mobility flows and the features of 368 prefecture-level cities, which are used to train and interpret the deep learning model.

3.1. Heavy truck GPS data

We use heavy truck GPS data to obtain the historical intercity mobility flows in China. The GPS dataset was obtained from the China Road Freight Supervision and Service Platform (https://www.gghypt.net/). This platform records the real-time geographic location of all heavy trucks in China and are used to monitor their traffic violations. We collected GPS trajectories of 2.7 million heavy trucks (with a maximum load of more than 12.5 tons) between 18 May 2018 and 31 May 2018. The trajectories were stored in the WGS-84 coordinate system with a sampling interval of 30 s. The number of records is greater than 41 billion.

The raw GPS data often contain a significant amount of erroneous and redundant information, which needs to be eliminated through a pre-processing stage. To obtain the intercity heavy truck mobility flows, we identify the intercity trip origins and destinations (OD) of each heavy truck from its GPS trajectories by using the method proposed by Yang et al. (2022b). In this trip OD identification method, heavy truck trajectory characteristics under the influence of GPS drift are first captured to identify all truck stops from GPS data, and then the temporal characteristics of truck activities, freight-related POI data and highway network GIS data are used to identify trip OD by distinguishing temporary stops (rest/fuel/traffic congestion) and freight activity stops (OD). After identifying the intercity trip OD of heavy trucks, we calculate the number of heavy truck trips between city pairs to obtain the intercity truck flows, which are used as target labels for model training and validation.

3.2. Freight POI data

We use freight POI data to obtain the features related to freight companies, markets and facilities of 368 cities in China. The freight POI data were crawled from Amap (https://lbs.amap.com) by using provided application programming interface (API). In the Amap application, developers store POIs in a hierarchical format by industry categories. According to the correlation between freight POIs and heavy truck freight activities (Amer and Chow, 2017; Dernir et al., 2014), we choose three categories of POIs. The first category is freight company, including metallurgy, medicine, telecommunication, construction, network, trade, decoration, machinery, mineral and factory. The second category is freight market, including supermarket, building material market, home appliance market, integrated market, industry park and agricultural base. The third category is freight facility, including transport hubs (e.g., train stations, airports and ports) and logistics nodes (e.g., warehouses and distribution centers). Next, we calculate the number of POIs of each category, and they make up the input features for deep learning model.

3.3. Geographic data

We use geographic data to obtain the features related to road networks and land uses of 368 cities in China. The geographic data were derived from OpenStreetMap (https://www.openstreetmap.org). We selected three types of roads, i.e., primary, secondary and motorway, and four classes of land uses, i.e., retail, residential, commercial and industrial. Next, we calculate the total length of each type of roads and total area of each class of land uses, and they also make up the input features for deep learning model.

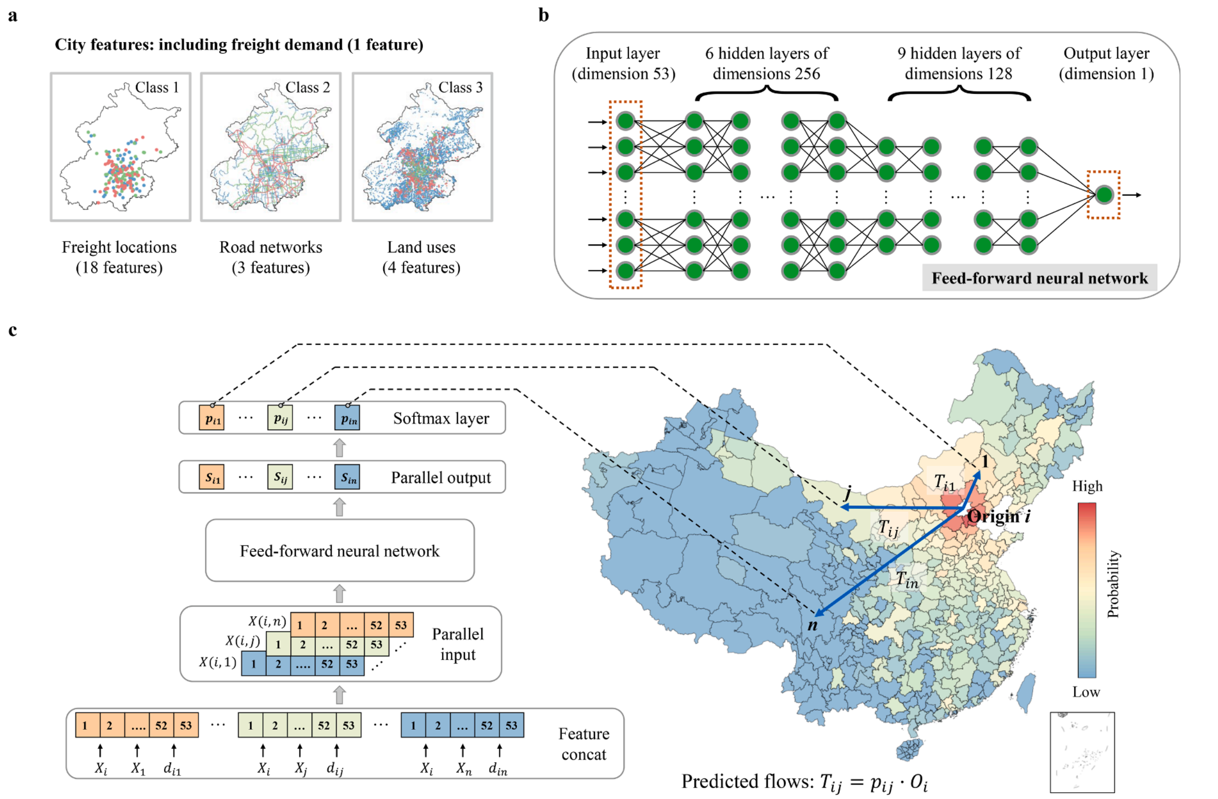

Fig. 1. Illustration of the architecture of Deep Gravity model. **a** City features. The colors in three panels indicate different types of locations, roads and land uses respectively. **b** Structure of the feed-forward neural network. **c** Example of estimating heavy truck mobility flows from an origin city i to all destination cities. Each region divided by solid grey lines is a prefecture-level city, i.e., a traffic analysis zone. The colorbar indicates the probabilities of a unit flow from origin city to each destination city.

4. Methodology

This work aims to accurately estimate heavy truck mobility flows between cities based on the framework of the Deep Gravity model that was originally proposed by Simini et al. (2021). We select 368 prefecture-level cities in China as the traffic analysis zones, and the geographical distribution of these prefecture-level cities is shown in Fig. 1**c**. The size of a prefecture city in China can vary significantly based on factors such as geographical location, topography, and administrative boundaries. On average, a prefecture city typically covers a land area ranging from approximately 5,000 to 10,000 square kilometers. However, it's essential to note that there is substantial variation within this range. Some smaller prefecture cities can have land areas as small as 2,000 square kilometers, while larger ones can extend to more than 20,000 square kilometers. The model performance is evaluated by comparing its results with those generated by traditional singly constrained gravity model. We further uncover the non-linear relationships between city features and intercity heavy truck mobility flows using explainable AI techniques to provide implications for logistics operations and city planning.

4.1. Architecture of Deep Gravity model

The Deep Gravity model, proposed by Simini et al. (2021), is a novel approach for modeling human mobility across geographical regions. This model extends the traditional Gravity model by incorporating a deep learning architecture to learn complex relationships between mobility patterns and geographical factors. To generate the flows from a given origin location i, the Deep Gravity model computes the probability p_{ij} of moving from the origin location i to each destination location j. Specifically, the model output is a n-dimensional vector of probabilities p_{ij} for $j = 1, \cdots, n$. The mobility flow T_{ij} from origin i to destination j is calculated as $T_{ij} = p_{ij} \cdot O_i$, where O_i is the population of origin i.

The Deep Gravity model has been widely utilized for predicting human travel demand. However, in the context of forecasting heavy truck travel demand between cities, there exists a gap in the understanding of the underlying factors that drive such movements. In this paper, we extend the original Deep Gravity model by incorporating a set of new and pertinent features during the model training process. These features are carefully selected to capture essential aspects related to urban freight transportation, including urban freight companies, market dynamics, freight facilities, characteristics of road networks, land use patterns, and the dynamics of freight demand. By integrating these features into the model, we aim to enhance its predictive accuracy and provide a more robust framework for forecasting heavy truck mobility flows between cities. The model framework is shown in Fig. 1.

4.1.1. Input layer

For an origin city i, the feature vector $\boldsymbol{X}_i$ of it, the feature vector $\boldsymbol{X}_j$ of each destination city j and Euclidean distance d_{ij} between them are concatenated as a sample $\boldsymbol{X}(i,j)$. All the samples $\boldsymbol{X}(i,j)$ for $j = 1, \cdots, n$, are fed into the network in parallel. To construct the feature vectors of cities, we select a wide range of features related to freight companies, markets, facilities, road networks, land uses and freight demand:

- Freight companies (10 features): total count of POIs for each possible freight-related company class, i.e., metallurgy, medicine, telecommunication, construction, network, trade, decoration, machinery, mineral, factory in a prefecture-level city;
- Freight markets (6 features): total count of POIs for each possible freight-related market class, i.e., supermarket, building material market, home appliance market, integrated market, industry park and agricultural base in a prefecture-level city;
- Freight facilities (2 features): total count of POIs for each possible freight-related facility class, i.e., transport hubs and logistics nodes in a prefecture-level city;
- Road networks (3 features): total length (in km) for each different types of roads, i.e., primary, secondary and motorway in a prefecture-level city;
- Land-use areas (4 features): total area (in km^2) for each possible land-use class, i.e., retail, residential, commercial and industrial in a prefecture-level city;
- Freight demand (1 features): sum of generated and attracted heavy truck flows of a prefecture-level city, i.e., city's total outflow and inflow.

Therefore, the number of features of each city is 26. The dimension of concatenated sample is 53 (26 features of the origin, 26 features of the destination and distance between origin and destination).

4.1.2. Intermediate layer

The intermediate layer consists of a feed-forward neural network. The network has 6 hidden layers of dimensions 256 and 9 hidden layers of dimensions 128 with LeakyReLu activation function (Nair and Hinton, 2010). The dimension of the output of this feed-forward neural network is 1.

4.1.3. Output layer

The input samples are fed into the feed-forward neural network in parallel, and the score s_{ij} for each input sample $\boldsymbol{X}(i,j)$ can be output in parallel. The higher the score s_{ij} for a pair of cities (i,j), the higher the probability to observe a trip from origin city i to destination city j. These scores are transformed into probabilities using a Softmax function, $p_{ij} = e^{s_{ij}} / \sum_k e^{s_{ik}}$, which transforms all scores into positive numbers that sum up to one. The estimated flow between two cities (i,j) is then obtained by multiplying the probability (i.

e., the model's output) and the origin's total outflow, i.e., $T_{ij} = p_{ij} \cdot O_i$.

4.1.4. Optimization configuration

The loss function is the cross-entropy

$$H = -\sum_i \sum_j \frac{T_{ij}^{obs}}{O_i} \cdot \ln(p_{ij}) \tag{1}$$

where T_{ij}^{obs} is observed truck flows from city i to j, O_i is truck flows out of the city i, T_{ij}^{obs}/O_i is the fraction of observed heavy flows from city i that go to city i, and p_{ij} is the model's probability of a unit flow from city i to j. The network is trained for 30 epochs with the RMSprop optimizer with momentum 0.9 and learning rate $5 \cdot 10^{-6}$.

It is noteworthy that GPS data are not used directly to estimate the output vector, but to capture aggregated intercity truck flows between city pairs, i.e., target labels for supervised machine learning model. The output vector of the neural network is estimated by feeding the concatenated features of city pairs in parallel and calculating the parallel output values by the Softmax function. The model-generated truck flow from an origin city to a destination city is calculated by multiplying the probability and the origin's total outflow. The empirical truck flows obtained by using GPS data are used to optimize model. Therefore, the trip origins and destinations of each heavy truck are first need to be identified, and then truck flows between city pairs are obtained to construct target labels.

4.2. Singly constrained gravity model

In this paper, we use the traditional singly constrained gravity model as a benchmark model to evaluate the performance of the Deep Gravity model. From the perspective of modeling ideas, the Deep Gravity model combines deep neural networks with the gravity model framework, provides a more sophisticated approach to capturing the complex relationships and dependencies in the data. Therefore, comparing the Deep Gravity model to the traditional gravity model can provide a baseline for evaluating the performance improvements achieved by our model in predicting aggregated intercity heavy truck flows.

The singly constrained gravity model is a mathematical model that is often used in transportation planning to estimate the number of trips that will occur between two locations (Lenormand et al., 2016). The model is based on the idea that the probability of a trip occurring between two locations is proportional to the attractiveness of the locations and inversely proportional to the distance between them. The heavy truck flows from origin city i to destination city j generated by singly constrained gravity model is given by

$$T_{ij}^{gra} = O_i \cdot p_{ij} = O_i \cdot \frac{D_j^{\beta} \cdot e^{-d_{ij}/\gamma}}{\sum_k D_k^{\beta} \cdot e^{-d_{ik}/\gamma}} \tag{2}$$

where O_i is origin's total outflow, p_{ij} is the probability to observe a trip (unit flow) from origin i to destination j, D_j is destination's total inflow, d_{ij} is distance between origin and destination, β and γ are parameters that can be estimated by maximum likelihood method (Sen, 1986). The model describes the flow probability based on two explanatory variables, i.e., freight demand (measured by destination city's total inflow) and distance between a pair of origin and destination cities.

4.3. Model performance evaluation

We evaluate the performance of Deep Gravity model and singly constrained gravity model by computing the similarity between observed flows and generated flows by models. The supervised deep learning model in this paper aims to predict intercity truck flows by incorporating various input datasets along with the corresponding target labels. In the model, the input datasets are derived from the city features related to freight companies, markets, facilities, road networks, land uses and freight demand. The target labels represent the empirical intercity truck flows, which are obtained from the GPS data. For a city pair, we obtain the observed aggregated heavy truck flows between these two cities from the individual-level GPS trajectories of heavy trucks. We compare the observed flows with model-generated flows for all city pairs to validate the model.

In the paper, we use two evaluation metrics. The first one is the common metric of Sørensen-Dice index, also called Common Part of Commuters (CPC) (Barbosa et al., 2018), and second one is commonly used Root Mean Square Error (RMSE) (Hyndman and Koehler, 2006). The *CPC* metric is calculated by

$$CPC = \frac{2\sum_{i,j}\min(T_{ij}^{obs}, T_{ij}^{model})}{\sum_{i,j}T_{ij}^{obs} + \sum_{i,j}T_{ij}^{model}} \tag{3}$$

where T_{ij}^{obs} is observed truck flows from city i to j, and T_{ij}^{model} is generated flows by model. The *CPC* always remains non-negative and falls within the closed range [0, 1]. A value of 1 indicates an ideal match between the generated and observed flows, while 0 signifies poor performance with no overlap. The *RMSE* metric is given by

$$RMSE = \sqrt{\frac{\sum_{i,j \neq i} \left(T_{ij}^{obs} - T_{ij}^{model}\right)^2}{N_{pair}}} \tag{4}$$

where N_{pair} is the number of city pairs. The *CPC* metric primarily focuses on comparing the presence or absence of flows in the commonalities, capturing the shared information between the two sets of flows. In contrast, the RMSE metric assesses the similarity of flow magnitudes. By incorporating the metrics of *CPC* and *RMSE*, we aim to provide a holistic evaluation of model performance considering not only the spatial presence of flows but also their magnitude and distribution.

4.4. Model interpretation

Machine learning models are often considered “black box” models, meaning that it can be difficult to understand how they arrive at their predictions because of the complex non-linear transformations between different layers (Molnar, 2020). Understanding why a model makes a certain prediction is crucial to interpret results.

In this study, we use SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017) to interpret the output of Deep Gravity model to understand how the input features contribute to the determination of intercity heavy truck movements. The fundamental concept of SHAP is rooted in cooperative game theory’s Shapley values (Strumbelj and Kononenko, 2014). These values are employed to quantify the relative importance of each feature, and gain insights into their interactions in influencing the model’s prediction. By calculating SHAP values, three different perspectives of interpretation can be provided. (1) Global feature importance: by aggregating SHAP values across all instances in the dataset, we can obtain a global measure of feature importance. The higher the average magnitude of a feature’s SHAP values, the more important that feature is in the model. This can help identify the most influential features in the Deep Gravity model. (2) Local feature importance: by examining SHAP values for individual instances (i.e., city pairs), we can understand how the contributions of each feature differ across different city pairs. This can help identify unique interactions or nonlinear relationships between features that might not be captured by a global measure of importance. (3) Feature interactions: we can calculate SHAP interaction values and visualize the joint distribution of SHAP values for pairs of features to understand how features interact with each other. By examining these joint distributions, we can detect interactions, such as synergistic or antagonistic

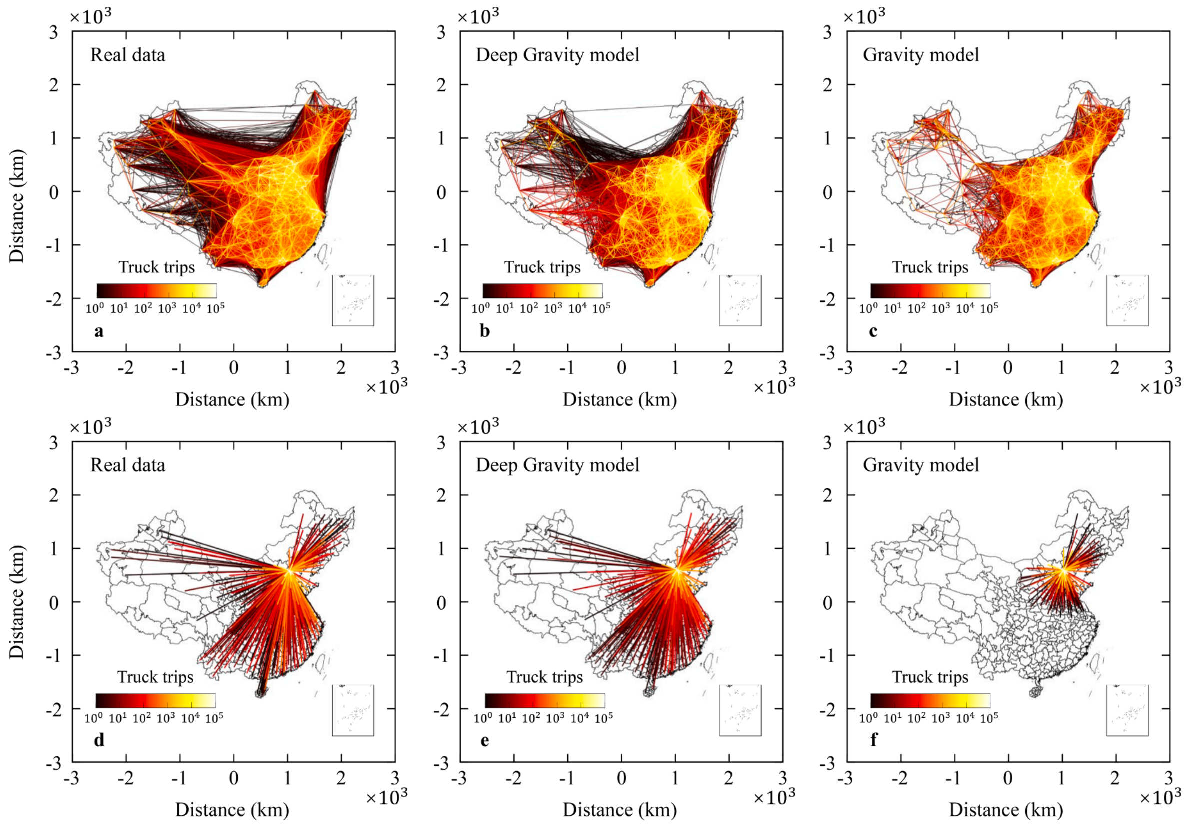

Fig. 2. Comparing the predictions of the Deep Gravity model and the singly constrained gravity model. **a-c** Observed and generated heavy truck mobility flows by models between all city pairs in China. **d-f** Observed and generated heavy truck mobility flows by models from the origin city (Beijing) to all destination cities. The colorbar indicates the number of truck trips between cities.

effects, between features.

5. Results

We use the data of city features and historical intercity heavy truck flows to train the Deep Gravity model, and obtain the generated flows. We first evaluate the performance of Deep Gravity model by comparing its results with the predicted results of singly constrained gravity model. Next, we use explainable AI techniques to interpret the output of Deep Gravity model, aiming to uncover the factors contributing to intercity heavy truck movements, heterogeneity of influencing factors across city pairs, and synergistic and antagonistic effects related to space.

5.1. Performance of the Deep Gravity model

We generate intercity heavy truck mobility flows by the Deep Gravity model and singly constrained gravity model, and compare them with real results to evaluate the performance of models, as shown in Fig. 2. To obtain the real heavy truck mobility flows between city pairs, we identify the trip origins and destinations of heavy trucks from GPS trajectory data and calculate the number of truck trips between different city pairs, i.e., real intercity truck flows. To generate the intercity truck flows by the Deep Gravity model, we train the model and generate the truck flows based on the features derived from a wide range of features related to freight companies, markets, facilities, road networks, land uses and freight demand. To generate the intercity truck flows by the singly constrained gravity model, we first calculate the total outflow and inflow of each city by using the real truck flows, and then generate the intercity truck flows according to gravity rules. The results suggest that the generated flows of Deep Gravity model are more similar to the real ones than those of singly constrained gravity model, both in terms of structure and distribution of flow values (see Fig. 2**a-c**). We can also find that traditional gravity model can provide reasonable predictions for high flows between cities, but do not perform as well when it comes to predicting mobility flows between smaller cities or those with low travel demand. Moreover, Fig. 2**d-f** show the generated flows from an origin city, i.e., Beijing, to all destination cities. The results indicate that traditional gravity model cannot provide accurate predictions for cities that are far apart compared to Deep Gravity model.

The poor performance of traditional gravity model is mainly due to its simplifying assumptions (Lenormand et al., 2016), i.e., the number of trips between two cities is positively related to freight demand and negatively related to distance. Therefore, the facilitating effect of freight demand is weaker between city pairs with lower travel demands, and the decaying effect of space is stronger between city pairs with longer distances. In contrast, in addition to freight demand and space, the Deep Gravity model integrates the effects of various features related to freight companies, markets, facilities, road networks and land uses, leading to a more accurate prediction. To quantify the accuracy improvement, we further compare the real flows and generated flow by models, and calculate the metrics of *CPC* and *RMSE*, as shown in Fig. 3. The results suggest the Deep gravity model performs significantly better than traditional model, emphasizing the importance of capturing the complex interactions between various features.

5.2. Factors contributing to intercity heavy truck movements

We use an explainable AI technique, i.e., SHAP (Lundberg and Lee, 2017), to interpret the output of Deep Gravity model, and to understand how the city features contribute to the determination of intercity heavy truck movements.

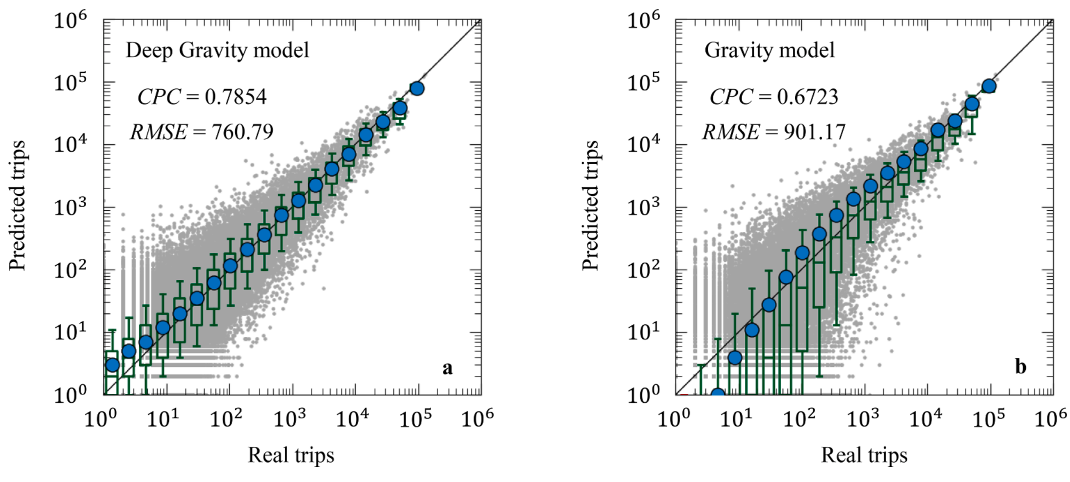

Fig. 3. Comparing the observed flows with the predicted flows for all city pairs in China. **a** Truck flows predicted by the Deep Gravity model. **b** Truck flows predicted by the singly constrained gravity model. The grey points are scatter plot for each pair of cities. The blue points represent the average number of predicted trips in different bins. The boxplots represent the distribution of the number of predicted trips in different bins of the number of observed trips. A box is marked in green if the line $y = x$ lies between 10 % and 91 % in that bin.

To get an overview of which features are most important for the output of model, we plot the SHAP values of every feature for every sample (see Fig. 4**a**) and average the absolute SHAP values across all samples (see Fig. 4**b**). Our dataset comprises a total of 53 features, including 26 features related to the origin, 26 features related to the destination, and the distance between the origin and destination. Integrating all 53 features into a single figure could result in a visually cluttered and challenging-to-interpret presentation. To enhance the visual coherence of the figure and facilitate a more accessible understanding of our findings, we have strategically opted to showcase the top 15 features with the highest SHAP values. These features hold the greatest influence over the model's predictions, making them pivotal in deciphering the driving factors behind the model's decision-making process. One of the features with the most significant impact on the model's predictions is geographic distance. As expected, a longer distance between the origin and destination results in a decreased flow probability, while a shorter distance leads to an increased probability. Furthermore, the freight demands of both origin and destination cities are crucial features to consider. When there is a higher freight demand in both the origin and destination cities, it typically indicates a larger volume of goods requiring transportation. This, in turn, tends to result in increased truck mobility flows. The revealed contributions of freight demand and geographic distance to intercity heavy truck movements are in line with the assumption of traditional gravity models. Besides these two features, there are many other factors that can influence truck mobility flows and their associated SHAP values.

The first class of influencing factors is the number of freight locations: an increased number of freight locations, including integrated markets, transport hubs, decoration companies and factories, in destination cities can lead to higher flow probability. This means when a city has numerous freight locations, it may be more attractive to freight carriers due to better infrastructure and more efficient distribution channels (Baker et al., 2023). The second category of influencing factors relates to the connectivity of road networks. Specifically, the total length of motorways in both origin and destination cities plays a significant role in determining the corresponding SHAP values. When there are more roads within the transportation network, the overall connectivity between different areas of the cities and their surrounding regions is enhanced. This improved connectivity facilitates smoother travel for trucks between the origin and destination cities. This improved accessibility can lead to more efficient distribution of goods and higher truck mobility flows, as trucks can reach their destinations more easily (Pirra et al., 2022). The third class of influencing factors is the area of industrial land-uses in origin and destination cities. A higher area of industrial land-uses may result in more distribution hubs or warehouses, leading to more efficient goods distribution and higher truck mobility flows between and within the cities (Cheng, 2022). In addition. a larger area of industrial land-uses in cities typically indicates a higher level of production activities, which can lead to increased demand for goods transport, contributing to increased truck mobility flows too.

5.3. Heterogeneity of influencing factors across city pairs

In the above, we quantify the global importance of city features and geographic distance. Here we explore the heterogeneity of influencing factors across city pairs to gain a deeper understanding of the factors that impact movements of heavy trucks between different cities.

We select a long-distance city pair (i.e., Beijing and Guangzhou) and a short-distance city pair (i.e., Xiamen and Fuzhou) (see Fig. 5**a**) and consider the two flows between each city pair, in which the freight demands of origin and destination city are similar. In such scenarios, the gravity model tends to generate two nearly identical flows between each selected city pair (e.g., from Beijing to Guangzhou and from Guangzhou to Beijing). This similarity arises from the equal distances and similar freight demands. However, the

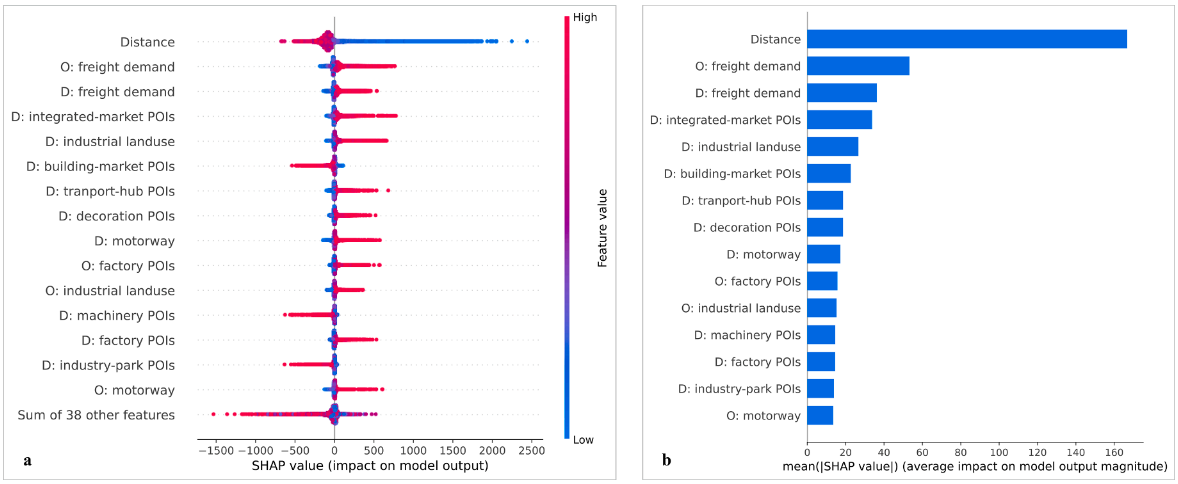

Fig. 4. Global measure of feature importance for the output of Deep Gravity model. **a** Distribution of SHAP values for all features. The vertical axis displays features, arranged from the most significant at the top to the least significant at the bottom. Features starting with "D:" and "O:" correspond to destination and origin city features respectively. Each point symbolizes an origin–destination pair, and the feature values for each origin–destination pair are indicated by colorbar. The horizontal axis indicates the SHAP value of the feature for a specific origin–destination pair. **b** Distribution of mean absolute value of SHAP values for each feature. The features are arranged vertically in order of importance.

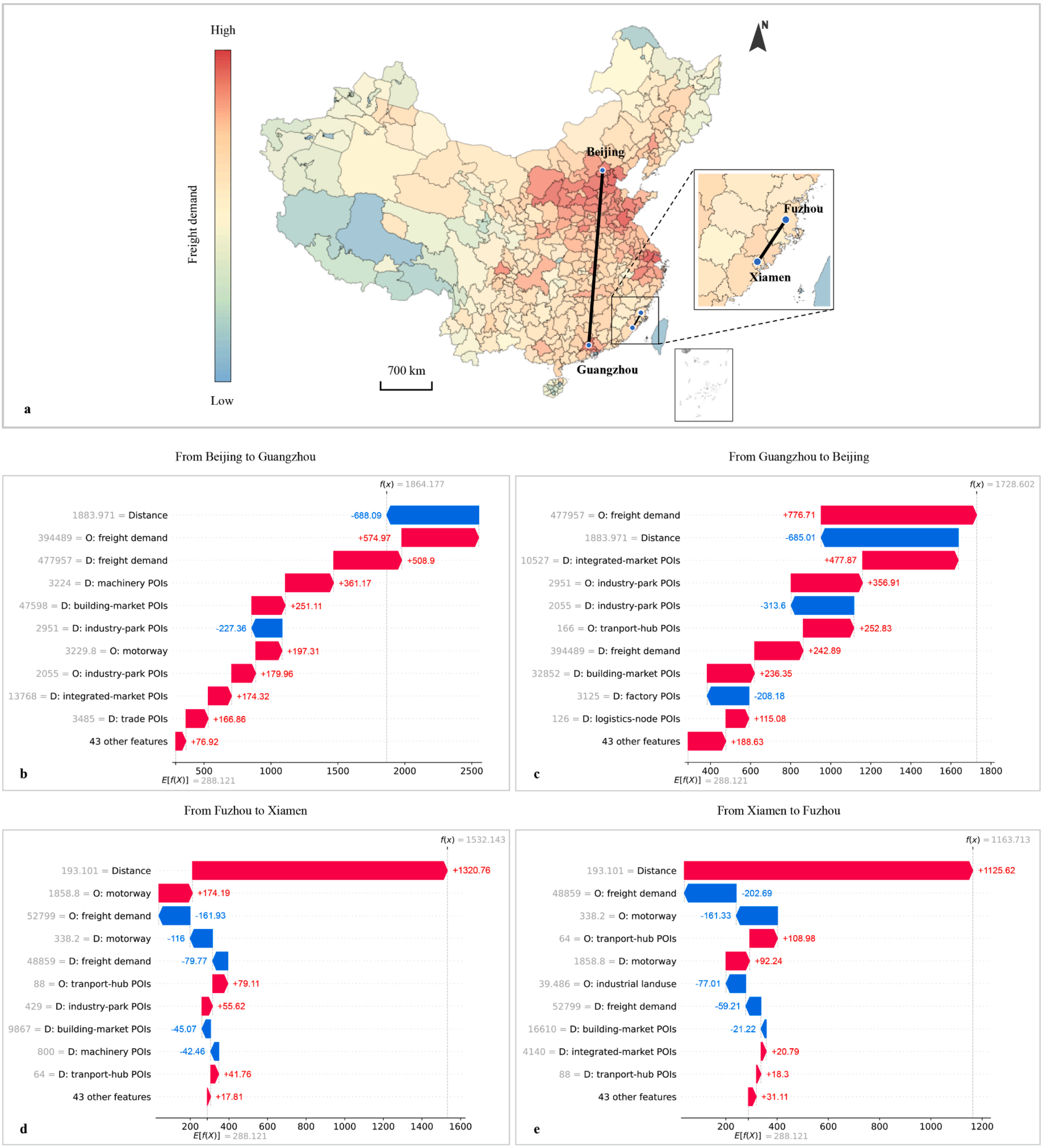

Fig. 5. Explanation of flow probabilities for city pairs. **a** Geographic position, shape, freight demand and distance between a long-distance city pair (i.e., Beijing and Guangzhou) and a short-distance city pair (i.e., Xiamen and Fuzhou). The colorbar indicates the freight demand of cities in China. **b** SHAP values for the two flows between Beijing and Guangzhou. **c** SHAP values for the two flows between Xiamen and Fuzhou.

Deep Gravity model takes a different approach by assigning distinct probabilities to these two flows. The corresponding SHAP values reveal that various factors, such as integrated markets, industry parks, and transport hubs, hold greater relevance in influencing the model's predictions compared to freight demands, as shown in Fig. 5**b-e**. Besides, the influence of these factors on the two flows between the cities in a city pair varies considerably. This reflects the diverse economic relationships (Luo et al., 2023) and interaction pattern heterogeneity (Shen et al., 2023) between different cities.

Furthermore, we can also observe the heterogenous effects of space. Specifically, for long-distance city pair (i.e., Beijing and Guangzhou), the feature of geographic distance is negatively contributing to the heavy truck movements, and the long-distance spatial interactions between cities mainly rely on the driver effects of city features related to freight demands, companies, markets and facilities (see Fig. 5**b-c**). In contrast, for short-distance city pair (i.e., Xiamen and Fuzhou), the positive contribution of geographic distance dominates and the feature of freight demand even contributes negatively (see Fig. 5**d-e**). This indicates shorter distances between city pairs may result in lower transportation costs, faster delivery times and increased economic integration, and drive the spatial interactions between cities significantly (Wu et al., 2021).

5.4. Synergistic and antagonistic effects related to space

In the above, we uncover the heterogenous effects of space on the movements of heavy trucks between different cities. In this section, we aim to understand what factors strengthen and weaken the heterogenous effects of space, and reveal their interaction effects.

To this end, we calculate the SHAP interaction values between city features and geographic distance, and obtain the corresponding joint distributions. We select four typical city features, i.e., number of integrated markets, area of industrial land-uses, number of transport hubs and length of motorway, and plot the joint distributions between these features and geographic distance, as shown in Fig. 6. We can find that for short-distance (e.g., < 300km) city pair, the greater the number of integrated markets, the larger the SHAP interaction values between this feature and geographic distance tends to be; but for long-distance (e.g., > 300km) city pair, the greater the number of integrated markets, the SHAP interaction values tend to be smaller (Fig. 6**a**). This suggests high number of integrated markets strengthen the effects of space in short distances (known as synergistic effects), but weaken the effects of space in long distances (known as antagonistic effects). As the number of integrated markets increases (i.e., the cities' markets become more interconnected), the flow of goods and services between the cities can improve. The close proximity of the cities ensures that transportation costs and delivery times remain manageable. This combination of shorter distances and a higher concentration of integrated markets creates a synergistic effect (Kim and Van Wee, 2011). This synergy enhances the benefits derived from each factor and improves overall efficiency. Consequently, it contributes to a stronger regional economy and facilitates an increased volume of heavy truck flows. In contrast, the potential efficiency gains from the interconnected markets are offset by the increased transportation costs and delivery times associated with the long distances between cities, thus resulting in an antagonistic effect (Legacy et al., 2017).

Moreover, we can also observe the similar interaction effects between other features, including area of industrial land-uses, number of transport hubs and length of motorway and geographic distance, as shown in Fig. 6**b-d**. These findings highlight the importance of considering the interactions between various factors when estimating intercity heavy truck mobility flows to ensure an appreciable level of accuracy.

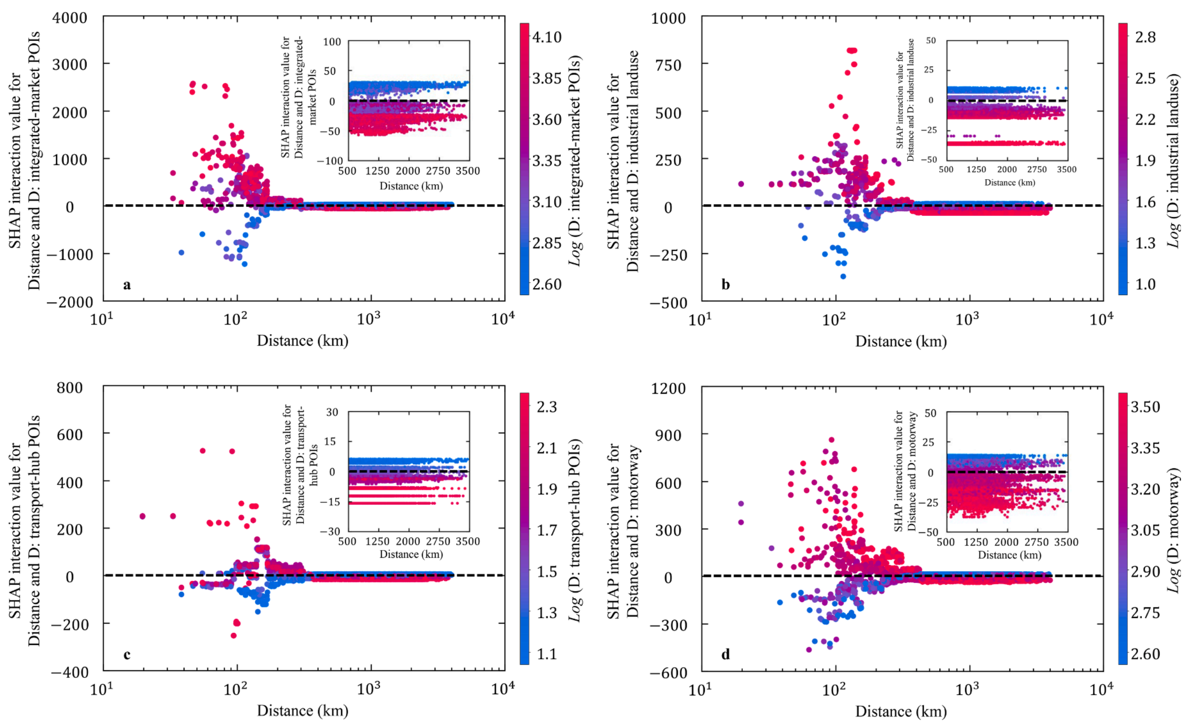

Fig. 6. Analyzing the interaction effects between four typical city features and geographic distance. Each point symbolizes a city pair, and the distances between city pairs are displayed on the horizontal axis in logarithmic scale. The color of points indicates the feature values converted by logarithmic functions for city pairs. The subplot in the upper right corner is a magnification of data distribution for long distances.

6. Discussion

In the paper, we estimate intercity heavy truck mobility flows based on the framework of Deep Gravity model. Compared to traditional gravity model, the accuracy is significantly improved, indicating the Deep Gravity model can capture the complex relationships of various features on the movements of heavy trucks between cities. There are many potential applications in logistics operations and urban planning by using the model in practice. For example, logistics company can use the model to help predict heavy truck freight demand between cities. Armed with this information, the logistics company can optimize resource allocation, such as trucks and drivers, in a more efficient manner. By understanding the patterns of heavy truck flows, they can allocate resources accordingly, ensuring sufficient capacity to meet the demand on busy routes. Additionally, the logistics company can use this predictive model to plan its future growth and expansion. By identifying areas with high demand for heavy truck freight, they can make strategic decisions about where to invest in new facilities, such as warehouses or distribution centers or expand their fleet to meet future demand. Besides, policymakers can use this information to plan transportation infrastructure improvements. By identifying the busiest routes and areas with the highest demand for heavy truck freight, they can plan improvements such as adding truck-only lanes, improving road surfaces to withstand heavier loads and creating better truck parking facilities. This can help reduce congestion, improve traffic flow, and promote economic growth.

We use explainable AI techniques to interpret the output of the model, and the findings can also provide valuable implications in reality. For example, the global measure of feature importance indicates that high number of freight locations, connectivity of road networks and area of industrial land-uses can lead to increased intercity heavy truck mobility flows. This finding can contribute to policy making for urban freight economy development. The first is to encourage the development of urban freight hubs (Cui et al., 2015), such as integrated markets, transport hubs and distribution centers in strategic areas. These hubs can help improve the efficiency of goods distribution. The second is to invest in the expansion and maintenance of road networks to improve connectivity of cities (Wang et al., 2022a). This can help foster the growth of businesses that rely on freight transportation. The third is to promote the clustering of industrial land-use areas and logistics parks in strategic locations, taking advantages of economies of scale (Combes, 2019). Understanding the importance of road network connectivity can inform transportation management decisions related to infrastructure planning (Ivut et al., 2021). It highlights the need to ensure efficient connections between key freight locations, such as industrial areas, ports, and distribution centers. Transportation authorities can focus on developing and maintaining well-connected road networks to facilitate smooth and uninterrupted truck movements, thereby improving overall freight transportation efficiency. The identification of a high number of freight locations as an influential factor suggests the significance of strategically locating facilities. Transportation management can use this information to guide decisions related to the placement of warehouses, distribution centers, and manufacturing plants, streamlining intercity heavy truck flows.

In addition, the model interpretation reveals the heterogeneity of influencing factors across city pairs. The influence of features on the movements of heavy trucks between different cities varies considerably. This finding inspires that policymakers should develop tailored policies and flexible regulatory frameworks (Munuzuri et al., 2012) that address the specific needs and characteristics of individual cities. This can involve creating city-specific regulations or providing local authorities with the autonomy to implement context-specific policies based on the unique factors affecting heavy truck movements in their jurisdictions. Urban planning needs to consider the specific characteristics and drivers of heavy truck movements for each city pair. Understanding the factors that influence truck flows in different contexts can help urban planners tailor infrastructure planning accordingly. For example, if one city pair experiences heavy truck movements primarily driven by industrial activities, urban planners can prioritize the development of industrial zones with appropriate road networks and access points. In contrast, if another city pair has truck movements driven by factors like retail or construction activities, urban planners can focus on designing transportation networks that cater to the unique requirements of those sectors.

Furthermore, the model interpretation uncovers the synergistic and antagonistic effects between various features, especially geographic distance. With this finding, policymakers should recognize the different effects that geographic distance has on intercity freight transportation and strive to balance policies that cater to both short and long-distance needs. This might involve investing in local distribution networks for short distances and supporting the development of more efficient long-haul transportation infrastructure. Specifically, to mitigate the antagonistic effects of geographic distance on long-distance freight transportation, policymakers should promote the use of intermodal transportation solutions (Agamez-Arias and Moyano-Fuentes, 2017), which combine various transportation modes to optimize the movement of goods. This can help reduce overall transportation costs, improve efficiency and lessen the environmental impact of long-distance intercity freight transportation. The interaction effects between various factors highlighted in the findings can inform network design and capacity planning in logistics operations (Bergmann et al., 2023; Wang et al., 2022b). For instance, if the number of transport hubs exhibits interaction effects with geographic distance, transportation managers can strategically plan the placement and capacity of transport hubs to cater to the demand for intercity heavy truck movements. This includes ensuring sufficient infrastructure, storage facilities, and logistical support to facilitate efficient freight transfers at these hubs. Considering the interaction effects between various factors is essential for effective route planning and optimization in transportation management. The findings suggest that the impact of geographic distance on intercity heavy truck mobility flows can vary depending on other factors, such as the number of integrated markets, area of industrial land-uses, number of transport hubs, and length of motorway. Transportation managers can leverage this information to identify optimal routes that minimize travel distance while accounting for the interactions between these factors. This can lead to more efficient and cost-effective transportation operations.

7. Conclusion

Accurate estimation of heavy truck mobility flows between cities can help transportation planners and policymakers develop strategies to ensure efficient infrastructure development, resource allocation and urban logistics planning. In the paper, we select 368 prefecture-level cities in China as the traffic analysis zones, and construct a deep learning network based on large-scale data related to intercity transport systems. The evaluation shows the performance (CPC is 0.7854) of Deep Gravity model is significantly higher than that (CPC is 0.6723) of traditional gravity model, indicating the Deep Gravity model can capture the complex effects of various features on the movements of heavy trucks between cities. We further use an explainable AI technique to interpret the output of Deep Gravity model. The results suggest the heterogeneity of influencing factors across city pairs, synergistic and antagonistic effects related to space. We found that high number of integrated markets strengthen the effects of space in short distances (e.g., $< 300\text{km}$), but weaken the effects of space in long distances (e.g., $> 300\text{km}$). These findings highlight the importance of considering the interactions between various factors when estimating intercity heavy truck mobility flows to ensure an appreciable level of accuracy.

The GPS data used in our study was aggregated into an OD matrix of heavy vehicle trips, covering a specific timeframe from May 18, 2018, to May 31, 2018. This timeframe represents a snapshot of heavy vehicle movements during this specific two-week period. Unlike passenger vehicles, heavy trucks involved in intercity transportation typically embark on journeys that extend over several days. As a result, the temporal dynamics of heavy truck travel differ significantly from daily or hourly patterns commonly observed in passenger vehicles. Therefore, this extended two-week timeframe is necessitated by the substantial distances they need to cover, logistical planning requirements, and the nature of freight operations.

Given the work in this paper, more meaningful future improvements and studies can be done. The first one of the promising future research directions is expanding the scope of features that might influence intercity heavy truck movements, such as economic factors, demographic characteristics, or freight transportation policies. Incorporating these additional features could help improve the accuracy and comprehensiveness of the model. The second one is exploring the applicability and generalizability of the model to different regions and countries, considering variations in transportation infrastructure, land use patterns, and local regulations. This could help determine if the model's performance is consistent across different contexts and provide insights into region-specific policy implications. The third one is investigating the temporal dynamics of intercity heavy truck movements, analyzing factors such as seasonal fluctuations, time-dependent transportation costs, or the impact of disruptive events (e.g., natural disasters or policy changes). Incorporating temporal factors into the model could provide a more comprehensive understanding of freight transportation patterns and inform more effective planning and decision-making. Moreover, we validate the applicability of the deep learning model using a singly constrained gravity model as a benchmark model. The availability of more travel information for individual trucks will provide the possibility of selecting activity-based models (Allen et al., 2014; Demissie and Kattan, 2022) with higher accuracy as benchmark models. This will enable further validation of the accuracy and universality of the deep gravity model, and provide more supports for practical applications. In addition, by acquiring multi-month or-year longitudinal data, we can extend research horizon to encompass a more extended temporal perspective. Over an annual timespan, we can further investigate the enduring trends and transformations of heavy truck freight demands between cities. This includes an examination of how truck flows evolve in response to economic growth, shifting business patterns, and alterations in transportation infrastructure. With the inclusion of a more extensive timeframe, we anticipate providing more robust policy implications for sustainable urban development and transportation management. Finally, while we have opted for the Euclidean distance in our current analysis due to its practical advantages, we acknowledge that it represents a simplification of the intricate environment of different city pairs. Future research could explore the differences and trade-offs between various distance metrics, such as network distances or travel times. Investigating these aspects would contribute to a more comprehensive understanding of the factors influencing intercity heavy truck freight activities.

CRediT authorship contribution statement

Yitao Yang: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft. **Bin Jia:** Conceptualization, Supervision, Funding acquisition, Project administration, Writing – review & editing. **Xiao-Yong Yan:** Conceptualization, Supervision, Funding acquisition, Methodology, Writing – review & editing. **Yan Chen:** Methodology, Writing – review & editing. **Dongdong Song:** Methodology, Writing – review & editing. **Danyue Zhi:** Writing – review & editing. **Yiyun Wang:** Writing – review & editing. **Ziyou Gao:** Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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