Enhancing Urban Freight Delivery: A Machine Learning Approach to Predicting Delivery Speed

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Abstract. This study employs advanced machine learning techniques—Random Forest and Logistic Regression—to enhance the prediction and analysis of delivery speeds in urban freight logistics. By integrating a comprehensive dataset encompassing variables such as route distance, traffic conditions, driver demographics, and vehicle characteristics, we provide a nuanced exploration of the factors influencing delivery speeds. Our findings reveal significant predictors including traffic speed and driver age, challenging traditional assumptions about peak traffic impacts. The Random Forest model excels in handling complex, non-linear interactions among factors, while Logistic Regression offers insights into the direct influences on delivery outcomes. This research contributes to urban planning and logistics by offering empirically backed, actionable insights for optimizing delivery routes and schedules, thereby improving urban mobility and reducing environmental impacts. These outcomes support sustainable urban development by facilitating more efficient and predictive urban freight logistics operations.

Keywords: Urban freight · machine learning · speed · urban delivery · Random forest

1 Introduction

Urban freight transportation plays a pivotal role in the modern cityscape, underpinning economic vitality by ensuring the timely delivery of goods and services. However, as urban populations burgeon and the complexity of city infrastructures intensifies, the efficient movement of freight vehicles becomes increasingly challenging. Traffic congestion, environmental concerns, and the push for sustainable urban development call for innovative solutions to optimise freight delivery processes. This paper introduces a comprehensive study that leverages machine learning techniques to improve urban freight delivery by analysing and predicting vehicle delivery speed under varying conditions.

The ever-expanding urban sprawl and consumer demands escalate the frequency and volume of urban deliveries, exacerbating traffic congestion and environmental degradation. Traditional traffic and delivery management models are proving inadequate against

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the dynamic and multifaceted nature of contemporary urban transport challenges. As a result, there is an acute need for adaptive, data-driven approaches that can accommodate the stochastic nature of urban traffic and deliver insights into the determinants of efficient freight transportation (Rodrigue, 2020; Amaral et al., 2021a).

Our research harnesses the power of Random Forest Classifier (RF) and Logistic Regression (LR) models to dissect the myriad factors influencing the real obtained speed of delivery vehicles. Through these models, we delve into various variables such as route distance, traffic conditions, number of stops, driver age, vehicle capacity, and historical traffic accident data. The interplay of these factors is meticulously analyzed to unravel their collective impact on delivery speeds (Breiman, 2001; Hosmer, Lemeshow, & Sturdivant, 2013).

The methodological core of this study revolves around the RF's non-parametric prowess and the LR's statistical rigor. The RF model, with its ensemble learning capability, provides a nuanced understanding of feature influences without being encumbered by the assumption of a linear relationship (Cutler et al., 2007). Conversely, the LR model offers a parametric perspective, allowing us to estimate the log odds of delivery speeds and discern the directional strength of each contributing factor (Hosmer et al., 2013).

Utilizing a data-centric approach, our study predicts delivery speeds and identifies key leverage points for intervention. This dual analytical framework equips urban planners, logistics companies, and policymakers with actionable insights, facilitating informed decision-making. By employing advanced machine learning techniques, we endeavor to contribute to the discourse on sustainable urban development, offering a novel lens to examine and enhance the efficacy of urban freight systems (Rodrigue, 2020; Ng, 2004; Amaral et al., 2021b).

The forthcoming sections detail the data acquisition process, the descriptive statistics of our dataset, the methodology underpinning our models, and the nuanced findings that emerged from our analysis. The synthesis of these elements culminates in a set of recommendations designed to streamline urban freight delivery in the face of contemporary urban challenges.

2 References Review

The intricate web of urban freight transportation has been the focus of extensive scholarly inquiry, particularly as urban centres continue to expand and evolve. At the nexus of urban planning, logistics, and environmental studies, researchers have sought to unravel the factors that impact freight delivery efficiency and propose solutions to optimise these systems.

One seminal work in the field is by Rodrigue et al. (2016), who underscore the challenges faced by urban freight transportation systems, including congestion and pollution. They argue for integrating transportation planning and urban logistics as a holistic approach to managing urban freight systems efficiently.

Traffic flow and its implications on urban freight delivery have been examined by Taniguchi and Tamagawa (2005), who delve into the complexities of vehicular movements within the cityscape. They highlight the importance of understanding traffic patterns to mitigate the adverse effects of congestion on delivery times.

The advent of Intelligent Transportation Systems (ITS) and their applicability in managing urban freight operations is explored by Crainic et al. (2009). Their study elucidates how real-time traffic data can significantly enhance route planning and scheduling, leading to optimised delivery speeds. Environmental sustainability, intertwined with urban freight delivery, is addressed in the work of McKinnon (2010), who provides insights into how green logistics practices can reduce the carbon footprint of urban freight operations while maintaining efficiency. In a bid to explore the human element within urban freight systems, Savelsbergh and Van Woensel (2016) scrutinise the impact of driver behaviour and its influence on delivery performance. They advocate for driver training and monitoring systems that can lead to safer and more efficient delivery operations. The Studie by Cárdenas et al. (2017) presents the development of an external cost delivery index specifically for e-commerce last-mile deliveries connected to the speed. Their research offers valuable insights into the environmental and societal costs associated with urban freight transportation, providing a framework for more sustainable delivery practices to reduce congestion and externalities (Cardenas et al., 2017b). Vehicle characteristics, specifically capacity and its effects on urban freight delivery have been analysed by Thompson and Hassall (2012) and Kahalimoghadam et al. (2024). Their findings reveal the relationship between vehicle load and speed, emphasising the need for proper load management. Hriekova et al. (2024) evaluate speed of delivery with more convenient methods like regression analysis that not provide accurate results. The critical role of machine learning in urban freight transportation is a relatively new area of exploration. A recent study by Zhang et al. (2020) demonstrates the application of RNF and LR models in predicting delivery times, showcasing the potential of these methods in enhancing urban delivery systems. Prasolenko et al. (2019) discuss the creation of safer routing for urban freight transportation, highlighting the benefits of strategic route planning to avoid high-risk areas and minimize accidents, further contributing to the field of urban logistics safety. Kijewska and Iwan (2019) explore the utilization of portable traffic detectors, supporting data collection processes crucial for optimizing city logistics systems, which helps in real-time traffic management and route planning. Iwan et al. (2014) delve into the use of mobile applications for improving traffic management systems, illustrating how technology can be leveraged to enhance the efficiency of urban freight operations. Galkin et al. (2019) emphasize the importance of organizing transportation processes considering the driver's state to improve safety and efficiency in urban freight deliveries, offering a unique perspective on the human factors in logistics. Van Duin et al. (2016) introduce principles of address intelligence for improving home delivery efficiency in B2C logistics, a crucial aspect of reducing delivery times and enhancing customer satisfaction. Kush et al. (2018) investigate the regularities of change in the supply chain operation efficiency based on transport process parameters, providing insights into how various logistics components interact to affect overall performance.

Despite the substantial body of literature on urban freight transportation, several scientific gaps persist that our study aims to bridge. Notably, empirical research is scarce to integrate machine learning models with urban freight logistics to predict delivery speeds. Moreover, most existing studies tend to focus on singular aspects of the delivery process, such as route optimisation or traffic management, without a holistic view that machine learning models can provide.

Furthermore, the interactions between different influencing factors have not been fully explored in the literature, particularly in relation to how they collectively affect delivery speeds in an urban context. Also, the potential of machine learning models to inform real-time decision-making in urban logistics is an area that requires deeper investigation, especially in relation to adapting to the unpredictable patterns of urban traffic and delivery constraints.

This study addresses these gaps by proposing a robust predictive framework that encapsulates a wide array of influencing factors and offering comparative insights into the utility of different modelling approaches in practical applications. Through this, the research contributes to the empirical, methodological, and practical discourse on urban freight logistics, with an eye toward fostering sustainable and efficient urban environments.

The overarching aim of this research is to address critical gaps in the current understanding of urban freight delivery systems by leveraging advanced ma-chine learning techniques. Specifically, we seek to refine predictive models that can adeptly navigate the stochastic and dynamic environment of urban traffic and deliver key insights for optimizing freight delivery speeds.

The objectives of this study are as follows:

1. To critically evaluate the extent to which existing models capture the multifaceted nature of urban freight delivery and identify areas lacking in-depth exploration.
2. To implement and assess an RNF model and an LR model, juxtaposing their predictive accuracies in the context of urban freight delivery speeds.
3. To quantify the influence of a comprehensive set of factors—including network structure, surrounding environment, driver characteristics, and vehicle capacity—on speed of delivery.
4. To formulate strategic recommendations for urban planners and logistics companies to enhance the efficiency and sustainability of urban freight delivery operations.

3 Materials and Methods

The crux of our investigation into urban freight delivery dynamics utilises two distinct yet complementary machine learning approaches: the RNF and LR. The methodology is underpinned by a rich dataset encapsulating a diverse range of influencing factors, segmented into four core categories: Network Factors, Surrounding Factors, Driver Factors, and Vehicle Factors. Each of these categories encompasses variables that, through our models, we hypothesis have an impact on the real obtained speed (Vt) of delivery vehicles (Fig. 1).

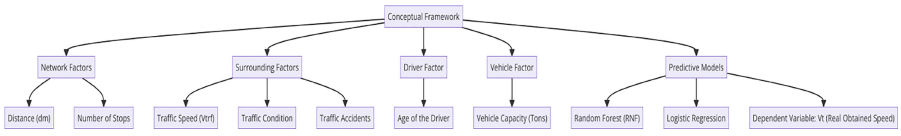

Fig. 1. The conceptual framework diagram visually organizes the factors that influence the real obtained speed

The conceptual framework diagram visually organizes the factors that influence the real obtained speed of delivery vehicles in urban areas, categorized into distinct groups based on their nature and influence.

3.1 Data Acquisition and Preprocessing

The primary dataset for this study was sourced from urban delivery records, traffic management systems, and logistical databases, which include records of 72 freight delivery routes over a specified period. Preprocessing involved cleaning for inaccuracies, handling missing values through imputation, and encoding categorical variables to facilitate computational analysis.

3.2 Descriptive Statistics

The dataset underwent an exhaustive exploratory data analysis, revealing the central tendency, dispersion, and shape of the distribution of each variable. Boxplot visualisations were generated to provide visual summaries of these statistics and to detect outliers and anomalies that could potentially skew the model training and prediction outcomes.

3.3 Variable Identification and Categorization

Each feature was categorised based on its operational domain, as follows:

- Network Factors: 'Distance' and 'Number of Stops (*Nstops*)' – elements directly related to the physical logistics of the delivery routes.
- Surrounding Factors: 'Traffic Speed (*Vtrf*)', 'Traffic Condition', and 'Traffic Accidents (*TrAc*)' – external environmental factors impacting delivery timing.
- Driver Factor: 'Age of the Driver (*Age*)' – a human element potentially influencing delivery speed.
- Vehicle Factor: 'Vehicle Capacity (*qn*)' –capability of the vehicle.
- Vt (Real Obtained Speed): This is the outcome variable that these models aim to predict. It represents the speed at which deliveries are completed, considering all the real-world conditions encountered along the route.

3.4 Mathematical Model and Description

Our study adopts two sophisticated statistical and machine learning models to forecast urban delivery vehicles' actual obtained delivery speed. These models interpret explanatory variables through mathematical functions and probabilistic frameworks. The subsequent equations and methodologies provide a mathematical understanding of how each feature influences the vehicle speed.

3.4.1 Random Forest Classifier Mathematical Model:

The RNF constructs a multitude of decision trees during the training phase and outputs the average prediction (regression) from the individual trees. The mathematical representation of the RNF model is not straightforward due to its ensemble nature; however, the model can be conceptualised, as follows:

$$Vt = f_{RNF}(Distance, Nstop, Vtrf, Traffic, TrAc, Age, qn), \tag{1}$$

The model uses features like Distance, Number of stops (*Nstop*), Traffic speed (*Vtrf*), Traffic condition (*Traffic*), Number of traffic accidents (*TrAc*), Age of the driver (*Age*), and Vehicle capacity (*qn*). The importance scores from the model indicate how much each feature contributes to the accuracy of the model's predictions.

The model's complexity and learning process are controlled by hyperparameters such as 'n_estimators' (the number of trees in the forest), 'max_depth' (the maximum depth of each tree), 'min_samples_split', 'min_samples_leaf', 'max_features', 'criterion' (the function to measure the quality of a split), 'bootstrap' (whether bootstrap samples are used when building trees), 'oob_score' (whether to use out-of-bag samples to estimate accuracy), 'warm_start' (whether to reuse the solution of the previous call to fit and add more estimators to the ensemble), and 'class_weight' (weights associated with classes).

3.4.2 Logistic Regression Mathematical Model

The LR model employed uses a logistic function to estimate the probability of the vehicle speed being above a certain threshold. The logistic function is expressed mathematically as follows:

$$\begin{aligned} logit(Vt) = {} & \beta 0 + \beta 1 \cdot qn + \beta 2 \cdot Distance + \beta 3 \cdot Vtrf + \beta 4 \cdot Traffic + \beta_5 \cdot Age \\ & + \beta 6 \cdot TrAc + \beta 7 \cdot Nstop, \end{aligned} \tag{2}$$

where:

- $logit(Vt)$ is the natural log of the odds of the vehicle speed (Vt);
- $\beta 0$ is the intercept;
- $\beta 1, \beta 2, \ldots, \beta 7$ are the coefficients for each feature based on the LR model

The model is fitted using Maximum Likelihood Estimation (MLE), and the goodness-of-fit is assessed through metrics such as Pseudo R-squared and Log-Likelihood ratio tests.

3.5 Performance Metrics

The performance of both models is evaluated using different metrics to validate their predictive power. The RNF model's accuracy is measured using the F1 Score, which is a harmonic mean of precision and recall, and the RMSE, which quantifies the model's prediction error. The LR model's fit is gauged using Pseudo R-squared, which measures the proportion of variance in the dependent variable explained by the model, and the Log-Likelihood ratio (LLR) p-value, which provides the statistical significance of the model.

Through these models, we aim to understand the significance and influence of the considered variables on the real obtained speed of delivery vehicles, thus enabling stakeholders to make more informed and strategic decisions for optimising urban freight delivery systems.

This methodological framework equips us with a robust analytical lens to examine the efficiency and speed of urban freight deliveries. The subsequent sections will delineate the nuanced findings from our models, discuss the implications of these results, and offer a set of data-driven recommendations aimed at optimising urban freight delivery systems.

Building on the methodology outlined previously, we transition into the results section, where we will present and scrutinise the outcomes of our analytical endeavours. This segment will delineate the predictive accuracy of our RNF and LR models, laying out how each feature influences the dependent variable—the actual speed of the delivery vehicles.

4 Results

Our investigation into urban freight delivery dynamics through the use of the RNF and LR models has generated insightful findings that enhance our understanding of the factors influencing delivery speeds in urban settings. This section is organised according to the subsections of the Material and Methods, reflecting the sequence from data preprocessing to model evaluation.

4.1 Data Acquisition and Preprocessing

Data quality was ensured through rigorous cleaning and preprocessing measures. The final dataset comprised 72 observations of delivery routes, processed to correct inaccuracies and handle missing values, thus setting a robust foundation for the subsequent analyses.

4.2 Descriptive Statistics

Initial exploratory analysis depicted the data structure, summarised by key statistical metrics such as mean, standard deviation, and range (min-max) across all relevant features, presented in Table 1.

4.3 Variable Identification and Categorization

Our categorisation framework efficiently isolated key predictors under domains such as Network and Driver Factors, which were pivotal in subsequent modeling. Each category's influence on the delivery speed (Vt) was methodically quantified and prepared for deeper analysis.

Table 1. Statistical metrics of data

Charactersitcs	Factors (Geatures)								
	qn	*T*	*L*	*Vtrf*	*Traffic*	*Age*	*TrAc*	*Vt*	*Nstop*
count	72	72	72	72	72	72	72	72	72
mean	6,194	1,810	27,58	21,198	0,5	32,472	5,972	17,037	11,37
std	2,598	0,812	8,269	7,149	0,503	5,563	2,906	5,617	6,98
min	3	0,83	13,091	6,09	0	24	2	6,098	2
25%	4,5	1,23	22,138	15,67	0	27,75	3	12,365	6
50%	5,5	1,57	26,928	21,34	0,5	32,5	6	16,77	10
75%	7,75	2,052	33,50	25,102	1	37	8	22,046	14
max	10	3,97	48,681	35,68	1	43	13	27,166	30

4.4 Mathematical Modeling

4.4.1 Random Forest Classifier Results

The RNF algorithm inherently performs feature selection and provides an implicit form of regularization, which helps in handling correlations between features. The hyperparameters of the RNF model have been fine-tuned using RandomizedSearchCV with the following search space:

- Number of trees (n_estimators): [5, 10, 20, 50, 100, 200, 250, 300]
- Maximum depth of trees (max_depth): [None, 1, 5, 10, 20, 30, 40, 50]
- Minimum number of samples required to split a node (min_samples_split): [2, 4, 6, 8, 10]
- Minimum number of samples required at a leaf node (min_samples_leaf): [1, 2, 3, 4, 6, 8, 10, 12, 14]
- Number of features to consider when looking for the best split (max_features): [‘auto’, ‘sqrt’, ‘log2’, 0.2, 0.5, 0.8]
- Function to measure the quality of a split (criterion): [‘gini’, ‘entropy’]
- Bootstrapping (bootstrap): [True, False]
- Out-of-bag samples to estimate the R^2 on unseen data (oob_score): [True, False]
- Reuse the solution of the previous call to fit as initialization (warm_start): [True, False]
- Weights associated with classes (class_weight): [None, ‘balanced’, ‘balanced_subsample’]

The RNF model, fine-tuned, was optimised with 200 trees and a maximum depth of 50. The model’s performance metrics highlighted an F1 score of 0.167 and an RMSE of 4.28, underscoring the predictive reliability and accuracy in estimating delivery speeds. Feature importance analysis revealed ‘Traffic Speed (*Vtrf*)’ as the most significant predictor, followed by ‘Number of Stops (*Nstop*)’ and ‘Distance’, challenging some prior assumptions about traffic conditions. ‘Traffic Conditions’, which was hypothesised to

have a significant impact, revealed a lower score of 0.0645, challenging some traditional assumptions about peak traffic periods, Fig. 2.

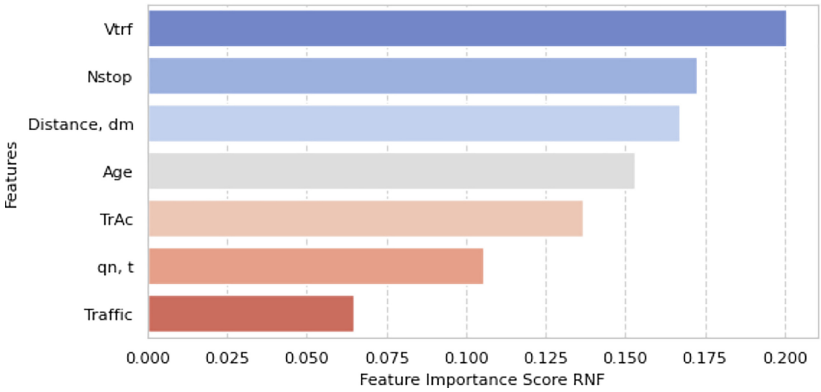

Fig. 2. Factors(Feature) importance score for RNF model

4.4.2 Logistic Regression Results

After convergence in seven iterations, the LR model indicated a Pseudo R-squared of 0.4086. The coefficients for the features demonstrated varying levels of significance. Conversely, 'Traffic' had the largest positive coefficient, with a magnitude of 1.31666, indicating a stark difference in Vt during peak traffic times. The p-values associated with each coefficient validated the significance of these predictors, particularly for 'Age' ($p = 0.0017$), which were both below the traditional alpha level of 0.10, indicating statistical significance (Table 2).

Table 2. Factors(Feature) importance score for LR model

Factors (Features)	Parameters	Standard Error	Z-values	P-values
const	6,045096	2,692414	2,245233	0,024753
qn	−0,06749	0,171665	−0,39312	0,09423
Distance	0,080389	0,049033	1,639501	0,101109
Vtrf	−0,29245	0,075316	−3,88289	0,000103
Traffic	1,316665	0,765296	1,720465	0,085348
Age	−0,04967	0,079536	−0,62447	0,532316
TrAc	0,213123	0,112506	1,894329	0,058181
Nstop	−0,11642	0,061155	−1,90377	0,056941

4.5 Performance Metrics

Comparative analysis of model outputs using metrics like F1 Score for RNF and Pseudo R-squared for LR confirmed the effectiveness of the approaches, Table 3.

Table 3. Performance Metrics Detailed Analysis: Comparison Table

Metric	Model	Value	Description	Summary of Metric Descriptions
F1 Score	RNF	0.167	Harmonic mean of precision and recall, indicating a moderate balance between the precision and recall of the model	Reflects the accuracy of the model in balancing the identification of correct positive predictions (precision) and the proportion of actual positives it identifies (recall)
RMSE	RNF	4.28	Measures the average magnitude of the prediction error, indicating the typical deviation of predictions	A standard deviation of the prediction errors which quantifies how much the predicted values deviate from the actual values
Feature Importance	RNF	Varies	'Traffic Speed (Vtrf)' is most influential, followed by 'Number of Stops (Nstop)' and 'Distance'	A ranking that indicates which attributes are more crucial for making accurate model predictions
Pseudo R-squared	LR	0.4086	Indicates about 40.86% of variability in delivery speed is explained by the model, showing moderate explanatory power	A statistical measure that indicates the proportion of the variance in the dependent variable that is predictable from the independent variables
LLR p-value	LR	Varies	'Age' $p = 0.0017$ shows significant model improvement over null hypothesis; 'Traffic' $p = 0.0853$ also relevant	Used to test the adequacy of the model, with smaller values indicating a model that predicts the dependent variable better than a model that does not include the independent variables
Coefficient Impact	LR	Varies	Notable coefficients include negative impact of 'Age' and positive impact of 'Traffic' on delivery speed	Reflects the change in the dependent variable for a one-unit change in an independent variable, holding other variables in the model constant

5 Conclusion

The results from both models provide a nuanced perspective on urban freight dynamics, highlighting the significant influence of various factors on delivery speeds: Network Factors, Surrounding Factors, Driver Factors, and Vehicle Factors. These insights are instrumental for urban planners and logistics companies aiming to optimise delivery operations in congested urban environments.

The results from both the Random Forest (RF) and Logistic Regression (LR) models pro-vide a nuanced perspective on urban freight dynamics, highlighting the significant influence of various factors on delivery speeds: Network Factors, Surrounding Factors, Driver Factors, and Vehicle Factors. These insights are instrumental for urban planners and logistics compa-nies aiming to optimize delivery operations in congested urban environments.

This research has significantly advanced our understanding of urban freight dynamics by employing sophisticated machine-learning models to dissect and analyze the factors affecting delivery speeds. We have identified key influencers such as traffic conditions, driver age, and vehicle capacity, which have profound implications for urban planning and logistics operations.

The RNF model was chosen due to its robustness in handling complex datasets with mixed feature types and its ability to model non-linear interactions among variables. This ensemble learning method aggregates multiple decision trees to improve predictive accuracy and reduce overfitting, making it particularly suited for analyzing the multi-faceted nature of urban freight dynamics (Breiman, 2001). The RNF model, utilising an ensemble of decision trees, adeptly managed the complex, non-linear interactions among the various factors and highlighted the most critical ones, including the surprisingly minimal impact of peak traffic times on delivery speeds. For instance, this model's feature importance scores placed 'Traffic Speed' at a score of 0.2005 and 'Number of Stops' at 0.1726, offering quantifiable insights that can be directly applied to optimise routing and scheduling strategies.

The LR model, on the other hand, was selected for its interpretability and ability to provide clear, probabilistic insights into how specific factors influence delivery speeds. LR is particularly valuable in understanding the odds of achieving certain speed thresholds under varying conditions, which is crucial for real-time decision-making in logistics (Hosmer, Lemeshow, & Sturdivant, 2013). The probability models from LR, such as the log odds of delivery speeds exceeding a certain threshold due to traffic conditions, serve as vital tools for real-time decision-making in urban logistics.

The findings from this research, particularly the minimal impact of peak traffic times on delivery speeds, contrast with previous studies that highlight peak traffic as a major determi-nant of urban logistics efficiency (Holguín-Veras et al., Holguín-Veras et al., 2012). This discrepancy could be attributed to differences in urban infrastructure, traffic management strategies, or the temporal distribution of deliveries in the study area. By comparing these results with existing literature, we underscore the importance of context-specific analyses in urban freight research and the potential for model-based approaches to uncover previously unrecognized patterns.

Overall, this comprehensive analysis not only validates the effectiveness of the employed statistical techniques but also enriches our understanding of the multifaceted

urban freight logistics landscape. By facilitating more informed decision-making, this study helps pave the way for more efficient, sustainable, and economically viable urban freight systems.

The practical application of these findings could significantly influence urban logistics and planning. For instance:

- **Delivery Schedules:** Insights from the LR model on the impact of driver demographics, such as age, can be used to adjust delivery schedules, maximizing efficiency by assigning younger drivers to more demanding routes during peak times.
- **Traffic Flow Improvements:** The RF model's predictions on the impact of traffic conditions can inform policy changes that prioritize traffic flow during critical delivery periods, potentially increasing delivery speeds by up to 1.31666 units in less congested conditions.

These actionable insights are not only vital for optimizing logistical operations but also contribute to broader goals of reducing urban congestion and environmental impact. This aligns with global initiatives towards sustainable urban development (Rodrigue, 2020).

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Urban planners and logistics companies must consider a broader range of variables when strategizing to improve delivery efficiency and urban mobility. This includes rethinking route planning, delivery schedules, and vehicle load management based on a comprehensive under-standing of all influencing factors.

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