Promoting Sustainable Mobility: Understanding Commuter Mode Choices through Predictive Modeling

Marzieh Afsari*[1], Ken Koshy Varghese[1], Lory Michelle Bresciani Miristice[2], Guido Gentile[3]

[1] PhD student, Department of Civil, Building and Environmental Engineering, Sapienza University, Italy

[2] Postdoctoral Researcher, Department of Civil, Building and Environmental Engineering, Sapienza University, Italy

[3] Associate Professor, Department of Civil, Building and Environmental Engineering, Sapienza University, Italy

SHORT SUMMARY

Understanding commuters' mode choice is crucial for promoting sustainable mobility and reducing car dependency. This study applies Multinomial Logit (MNL) and Neural Network (NN) models to survey data from employees in Rome, Italy, ensuring a fair comparison through identical preprocessing and evaluation metrics. Results show that while the NN model achieves slightly higher accuracy, statistical tests confirm the difference is not significant. Elasticity analysis in the MNL model examines key determinants influencing commuters' decisions and provides interpretable insights into travel behavior. These findings demonstrate that the MNL model delivers strong predictive performance while maintaining greater interpretability. This reinforces the relevance of traditional econometric models in transportation research, particularly for policy applications where explainability is essential.

Keywords: Mode choice, Neural networks, Multinomial Logit, Sustainable commuting.

1. INTRODUCTION

Commuters play a pivotal role in traffic flow, as they constitute a major share of travelers. Unlike non-commuters, whose travel behavior is more flexible, commuters exhibit stable long-term travel patterns tied to work or school commitments (Xiong et al. 2024). Understanding commuting patterns is crucial for transportation planning and sustainability policies. Additionally, traffic congestion harms transportation efficiency and well-being, increasing stress and reducing job satisfaction (Wener and Evans 2011).

Mode choice modeling is essential for understanding and predicting travel behavior. Traditional Discrete Choice Models (DCMs) are valued for their interpretability and theoretical foundation in explaining individual decisions (Hillel et al. 2021). In Machine Learning (ML) terms, a Random Utility Model (RUM) functions as a supervised probabilistic classifier, predicting mode choice probabilities from a finite dataset with ground-truth labels. ML classification algorithms, which excel in transportation tasks like safety assessment and demand prediction (M. Afsari et al. 2024; Eldafrawi et al. 2024), capture non-linear patterns without predefined utility specifications,

offering greater flexibility than RUMs. ML enhances accuracy, while DCMs prioritize interpretability through predefined variables (Martín-Baos et al. 2023).
Model selection depends on dataset characteristics, as shown by (García-García et al. 2022)). Since no single model is universally superior, we apply both Multinomial Logit (MNL) for its interpretability and Neural Networks (NN) for its power in capturing complex, non-linear relationships, to assess their effectiveness in predicting mode choice and supporting sustainable transportation policies of commuters in Rome, Italy. This study makes several key contributions:

- *Comparative Analysis of ML and Econometric Models:* Systematically compares MNL and NN models for mode choice prediction, addressing existing methodological gaps highlighted in prior literature; ensures consistency through a structured preprocessing pipeline, cross-validation, and benchmarking for rigorous model comparison.
- *Data Balancing Techniques*: Evaluates the impact of balancing strategies on mode choice datasets, which are often imbalanced.
- *Enhanced Interpretability*: Uses elasticity and marginal effect analysis in MNL to quantify key variables' influence on commuting choices, bridging the gap between predictive power and interpretability.
- *Sustainable Mobility Insights*: Identifies factors driving the shift toward sustainable transport, offering policy recommendations to reduce car dependency.

The paper is structured as follows: Section 2 details preprocessing and modeling framework; Section 3 presents the dataset, experimental results and model comparisons; Section 4 concludes with policy implications and future research directions.

2. METHODOLOGY

An MNL and an NN model were developed using a structured pipeline for fair comparison, as illustrated in Figure 1. Both models use the same preprocessing steps, train-test splitting, and evaluation metrics. They undergo confusion matrix evaluation and out-of-sample accuracy assessment, ensuring a consistent evaluation framework.

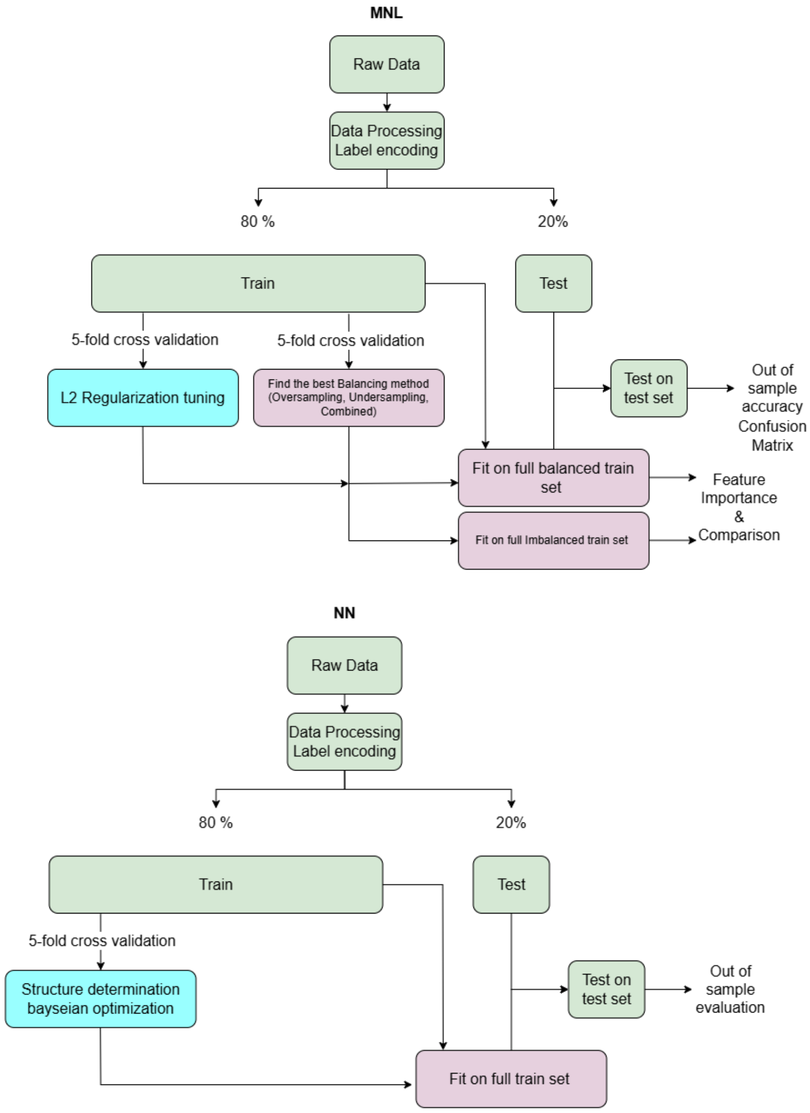


Figure 1: MNL and NN modeling workflows for mode choice prediction.

MNL Model

Unordered choice models are based on utility maximization theory, where individuals select the alternative that provides the highest utility. Since utility is not directly observable, the random utility theory is applied (Ben-Akiva and Lerman 1985), decomposing utility into a deterministic component and a random error term. The deterministic component $V_{n,i}$ captures observable attributes of the alternative i and individual characteristics n and is expressed as $V_{n,i} = f\left(B, x_{n,i}\right)$, where B represents the estimated parameters and $x_{n,i}$ the explanatory variables. When error terms follow an independently and identically distributed (IID) Type 1 Extreme Value distribution, the probability $P_{n,i}$ of individual n selecting alternative i is given by the MNL model:

$$P_{n,i} = \frac{e^{V_{n,i}}}{\sum_{j=1}^{J} e^{V_{n,j}}}. \tag{1}$$

The B parameters are determined by maximizing the following log-likelihood (LL) function, where $y_{(n,i)}$ is 1 if the decision-maker n chooses the alternative i:

$$LL(B) = \sum_{n=1}^{N} \sum_{i} y_{n,i} \ln(P_n, i)\,. \tag{2}$$

In this study, mode choice probability is modeled as a function of 46 independent variables, assuming a linear utility function within the random utility maximization framework. The model applies 5-fold cross-validation to fine-tune L2 regularization. Model estimation is performed using the Newton algorithm with trust region for simple bound constraints to ensure efficient convergence. The analysis is conducted in Python using the Biogeme library (Bierlaire 2025), a widely used tool for discrete choice modeling. As mode choice distribution is imbalanced, as shown in Figure 2, a balancing technique was applied to mitigate bias toward majority classes and improve model performance. Rezaei et al. (2021) demonstrated in their study that calibrating models on balanced data preserves the interpretability of logit models, making it a valid approach for improving model robustness.

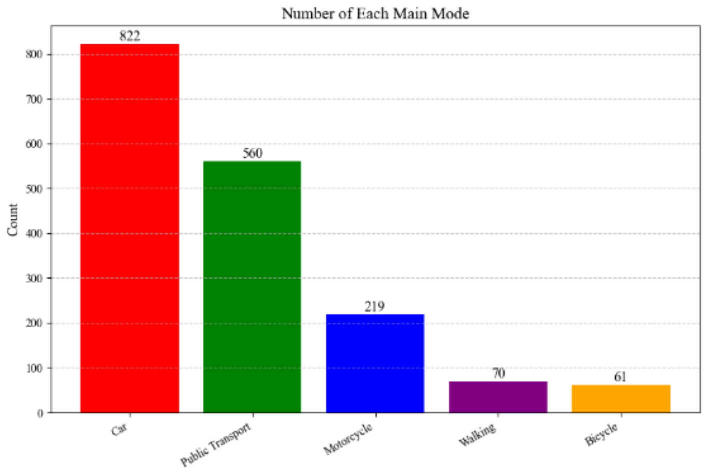


Figure 2: Distribution of commuting modes.

NN Model

NN operates as a system of linear equations where weights (X) and biases (b) connect neurons, with each neuron undergoing a nonlinear transformation as described in Equation (3). Here, Z_i represents the logit score of class i. The network parameters are optimized using the maximum likelihood principle, minimizing cross-entropy or maximizing LL. In multi-class classification, the final layer typically uses a softmax activation function (Equation (4)), which normalizes outputs between 0 and 1, ensuring that the predicted probabilities sum to 1 across all choices.

$$z_i = f(W * x + b) \tag{3}$$

$$P(i|x) = \frac{e^{z_i}}{\Sigma_i e^{z_i}} \tag{4}$$

Figure 3 illustrates the NN architecture for mode choice prediction processes various travel-related attributes, including work-related factors, travel behavior, mode-specific attributes, and opinions. The network includes input and two hidden layers using ReLU activation. Dropout rates of 24% and 10% are applied to reduce overfitting. The output layer uses a softmax activation function to classify commuting modes, predicting probabilities for car, motorcycle, walking, bicycle, and public transport. The model is trained with sparse categorical cross-entropy loss and optimized using Adam, ensuring efficient learning and stable convergence through forward and backward propagation. The model uses Bayesian optimization to determine the optimal architecture, and a 5-fold cross-validation enhances generalization.

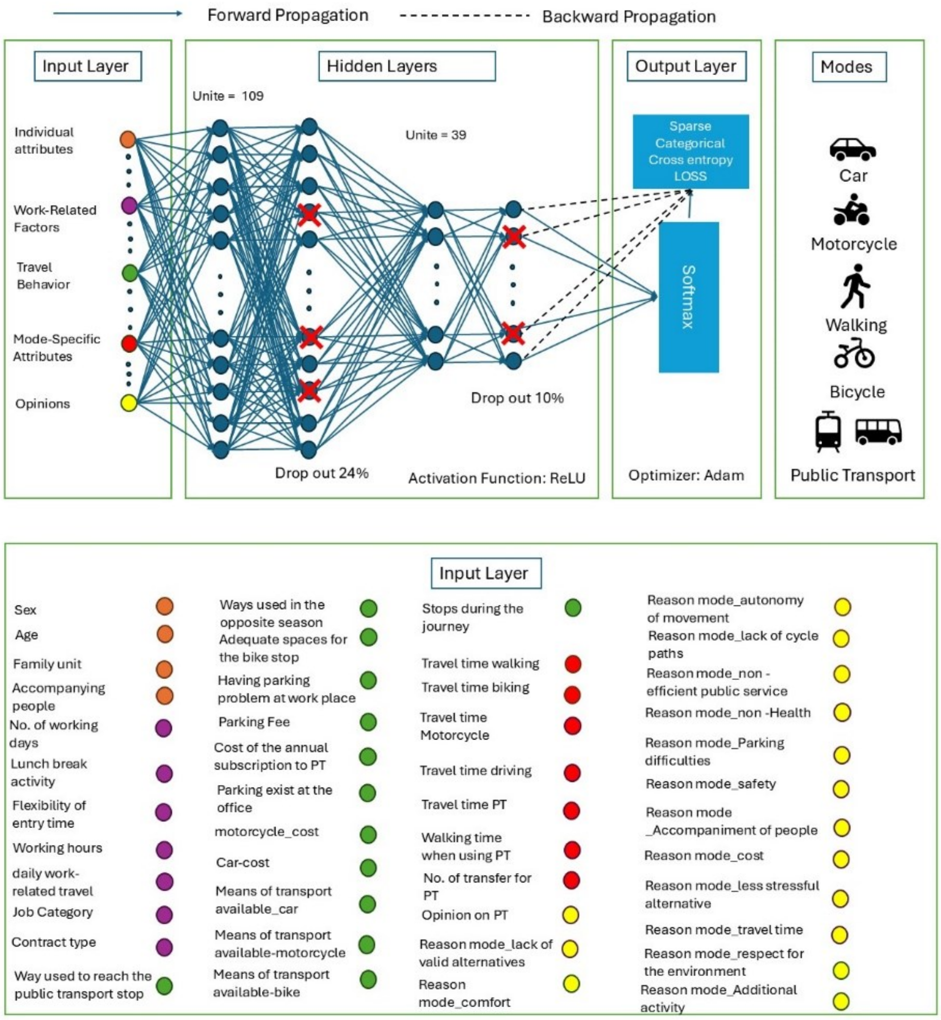


Figure 3: Neural network architecture for mode choice prediction.

3. RESULTS AND DISCUSSION

Data Preprocessing

The study uses survey data from 2023, collected across 31 companies in the Rome metropolitan area as shown in Figure 4. Initially, 2,887 employees participated, but 477 respondents living or working outside urban Rome were excluded to focus on sustainable commuting policies within the city. Missing values were managed by removing questions with less than 10% response rates and applying mode and mean imputation where necessary. After data cleaning, the final dataset included 1,688 valid responses from 30 companies, with 46 variables available for analysis.

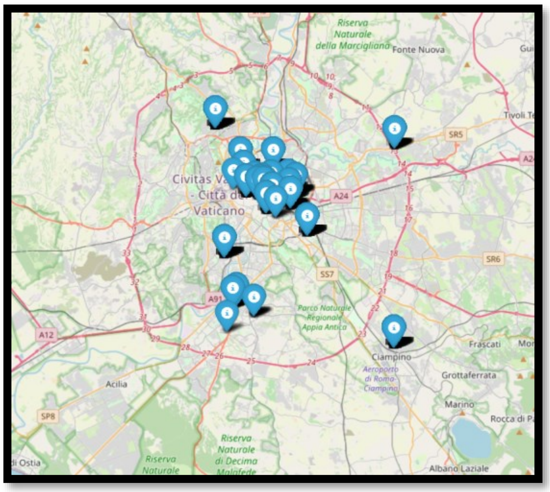


Figure 4: The location of companies.

The dataset includes five primary commuting modes (Figure 2), with travel times calculated using the Google Maps API based on employees' recorded departure times. These calculations account for real-time traffic congestion during morning peak hours. To ensure consistency, Wednesdays (20th Nov 2024) were chosen as the reference day for analysis. Flexible workers avoid peak congestion, so travel time was the main measure. Motorcycle travel time, not in Google Maps, was estimated at 80% of car travel, reflecting a 20% faster commute in urban areas.

The distribution of transportation mode usage varies by gender and age (Figure 5). Both men and women primarily use cars and motorcycles for commuting, with a notable portion relying on public transport, while walking and cycling remain minimal. Younger individuals, especially those under 30, are more likely to use public transport, whereas those over 40 show a stronger preference for cars. This trend corresponds with family unit sizes (Figure 6), as younger individuals tend to belong to smaller households, while older individuals, particularly those over 40, are more likely to have larger families, which may influence their commuting choices.

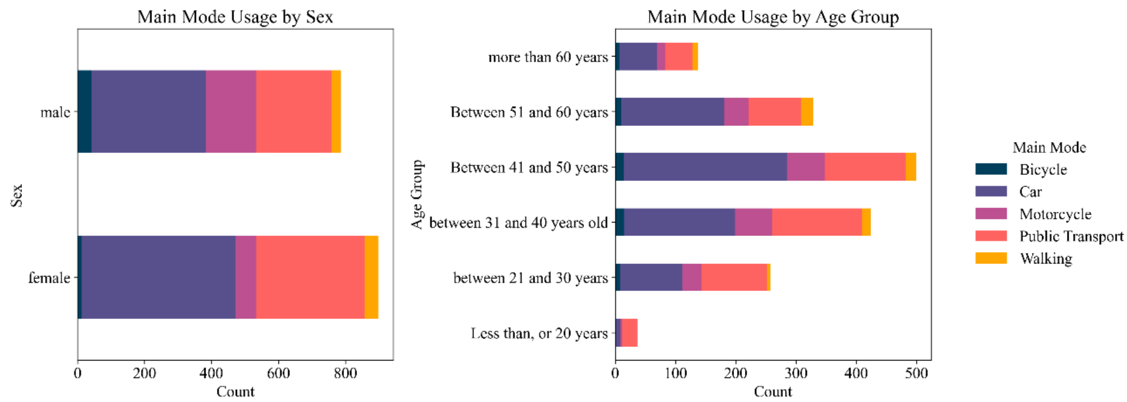


Figure 5: Mode choice distribution by sex (left) and age groups (right).

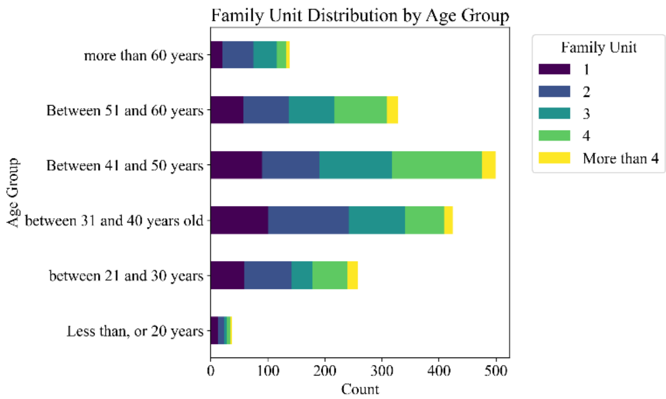


Figure 6: Family unit distribution across different age groups.

Data balancing impact

To prevent overfitting in the MNL model, a 5-fold cross-validation was performed, and the results are shown in Table 1, with the best performance achieved at L2 = 0.001. To address data imbalance, oversampling, under-sampling, and a hybrid approach were tested. Table 2 shows that oversampling provided the highest performance, enhancing model robustness by generating synthetic samples for minority classes. The hybrid approach also performed well but with slightly lower accuracy and F1-score. Based on these results, oversampling was chosen as the preferred balancing method for model training

Table 1: Hyperparameter tuning results for L2 regularization.

L2	Avg. Accuracy	Avg. Precision	Avg. Recall	Avg. F1 score
0.0001	0.8566	0.8567	0.8566	0.8551
0.0005	0.8578	0.8577	0.8578	0.8558
0.001	**0.8614**	**0.8619**	**0.8614**	**0.8583**
0.01	0.8436	0.8442	0.8436	0.8334

Table 2: Comparison of different balancing methods.

Method	Avg. Accuracy	Avg. Precision	Avg. Recall	Avg. F1-score
Random over-sampling	**0.9158**	**0.9158**	**0.9158**	**0.9144**
Random under-sampling	0.7907	0.8043	0.7907	0.7863
Hybrid sampling	0.9000	0.9037	0.9000	0.8948

To assess the impact of data balancing on the MNL model, predictions were compared using imbalanced and balanced test datasets. The model trained on imbalanced data achieved the highest overall performance as shown in Table 3 and Figure 7, particularly excelling in predicting the majority class (car) with minimal misclassification. However, minority classes like walking and bicycling had higher misclassification rates, reflecting the model's bias toward the dominant mode. After applying data balancing techniques, overall accuracy declined slightly, but the model improved in predicting minority classes, reducing class bias. This highlights a trade-off: balancing enhances predictions for underrepresented modes but slightly reduces accuracy for the dominant class. The findings suggest that while imbalanced data yields higher overall accuracy, it introduces bias by favoring the majority class.

Table 3: Comparison of MNL performance on balanced and imbalanced test datasets.

Dataset	Accuracy	Precision	Recall	F1-score
Balanced	0.7928	0.8184	0.7928	0.7991
Imbalanced	**0.8372**	**0.8339**	**0.8372**	**0.8333**

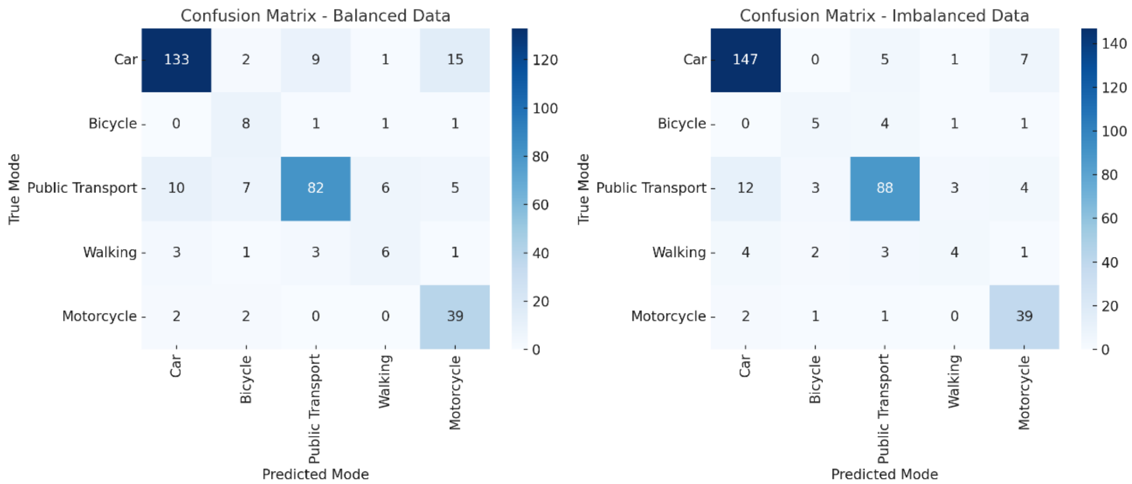
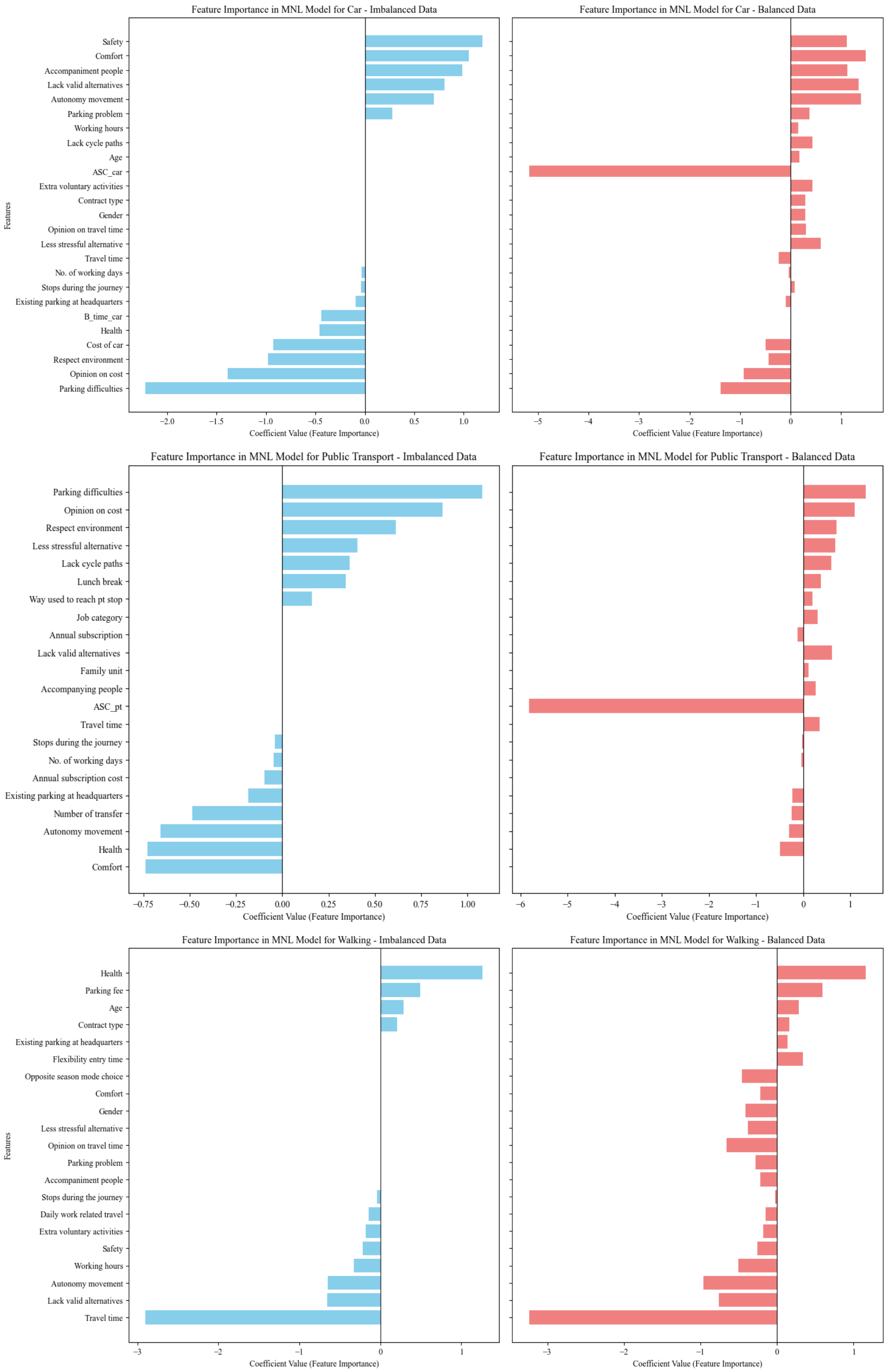


Figure 7: Confusion matrices for MNL on balanced (left) and imbalanced (right) test data.

To assess the impact of data balancing, the Cosine Similarity Metric was used to compare results from balanced and imbalanced datasets, following the approach of (Rezaei et al. 2021). Cosine similarity measures the orientation of vectors rather than their magnitude, making it useful for comparing feature importance distributions. Defined mathematically in Equation 5, its values range from -1 to 1, where 1 indicates identical vectors, 0 signifies no similarity, and -1 means they are completely opposite. This metric helps evaluate how balancing affects the consistency of feature importance in mode choice modeling.

$$Sim(x, y) = \frac{x \cdot y}{\|x\| \cdot \|y\|} \tag{5}$$

The computed cosine similarity of 0.925 indicates a strong similarity between the balanced and imbalanced models. However, key issues arise in mode choice analysis (Figure 8), particularly for public transport and car modes, where the alternative-specific constant (ASC) is disproportionately high in the balanced dataset, suggesting the model compensates for an inability to capture actual choice behavior. While variable relationships remain consistent across models, balancing the dataset distorts feature importance by overestimating the influence of some statistically insignificant variables. This can lead to misleading conclusions about factors affecting mode choice. To maintain accuracy and preserve the true significance of explanatory variables, the analysis continues with the imbalanced dataset, which better reflects real-world commuting behavior.


Feature Importance in MNL Model for Car - Imbalanced Data
Feature Importance in MNL Model for Car - Balanced Data
Features
Safety
Comfort
Accompaniment people
Lack valid alternatives
Autonomy movement
Parking problem
Working hours
Lack cycle paths
Age
ASC_car
Extra voluntary activities
Contract type
Gender
Opinion on travel time
Less stressful alternative
Travel time
No. of working days
Stops during the journey
Existing parking at headquarters
B_time_car
Health
Cost of car
Respect environment
Opinion on cost
Parking difficulties
Coefficient Value (Feature Importance)
Feature Importance in MNL Model for Public Transport - Imbalanced Data
Feature Importance in MNL Model for Public Transport - Balanced Data
Parking difficulties
Opinion on cost
Respect environment
Less stressful alternative
Lack cycle paths
Lunch break
Way used to reach pt stop
Job category
Annual subscription
Lack valid alternatives
Family unit
Accompanying people
ASC_pt
Travel time
Stops during the journey
No. of working days
Annual subscription cost
Existing parking at headquarters
Number of transfer
Autonomy movement
Health
Comfort
Feature Importance in MNL Model for Walking - Imbalanced Data
Feature Importance in MNL Model for Walking - Balanced Data
Health
Parking fee
Age
Contract type
Existing parking at headquarters
Flexibility entry time
Opposite season mode choice
Comfort
Gender
Less stressful alternative
Opinion on travel time
Parking problem
Accompaniment people
Stops during the journey
Daily work related travel
Extra voluntary activities
Safety
Working hours
Autonomy movement
Lack valid alternatives
Travel time

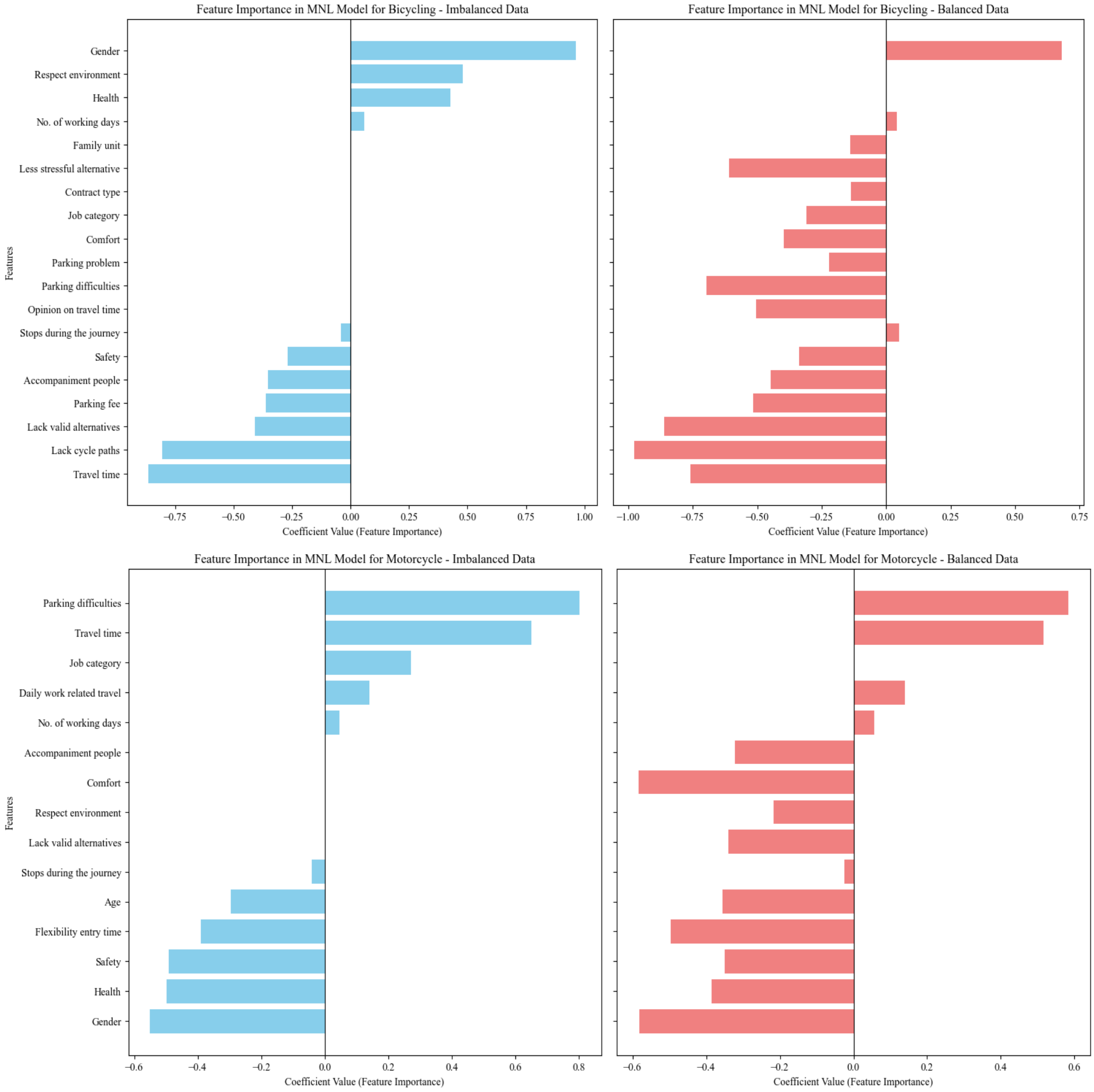


Figure 8: Comparison of feature importance in MNL for each mode under imbalanced and balanced data assumptions.

Comparing the MNL and NN Performance

Table 4 compares the performance of the NN and MNL models, showing that the NN model outperforms the MNL model by approximately 3% across all evaluation metrics. To assess whether this difference is statistically significant or due to randomness, a paired t-test was conducted on precision values from five cross-validation folds. The test resulted in a t-statistic of -2.40 and a p-value of 0.074, indicating that the difference is not statistically significant at the 0.05 threshold. While the NN model achieves higher precision, the improvement cannot be conclusively attributed to a fundamental difference in performance. This suggests that for medium-sized datasets, a well-implemented MNL model remains a viable alternative despite the NN model's slight advantage.

Table 4: Comparison of the results of NN and MNL.

Method	Accuracy	Precision	Recall	F1-score
NN	0.8663	0.8715	0.8668	0.8659
MNL	0.8372	0.8339	0.8372	0.8333

Sustainable Mobility Insights

To encourage a shift from car and motorcycle use to more sustainable transport modes, it is essential to understand how individuals respond to changes in travel-related attributes. The elasticity and marginal effect analysis (Figure 9) of the model highlights key factors influencing mode choice. Direct elasticities measure how each mode responds to changes in its attributes. Marginal effects provide absolute probability changes when a variable is modified. Combined with feature importance analysis (Figure 8), these findings offer critical insights for policy interventions.

Reducing car use requires economic, infrastructure, and behavioral interventions. The results show that increasing parking fees is highly effective in discouraging car use, especially when coupled with dynamic pricing during peak hours or in high-demand areas. Reducing the convenience of car use, such as repurposing parking spaces for bicycle lanes or pedestrian zones, car-free zones, and high-occupancy vehicle (HOV) lanes, further motivates shifts toward alternative modes. Paired with an efficient public transport system, these policies can significantly decrease car dependency.

Environmental and health concerns also influence mode choices but to a lesser extent than economic factors. Awareness campaigns, employer incentives, and eco-friendly mobility programs can enhance these effects, fostering long-term behavior change. Motorcycle use, though sensitive to travel time and parking challenges, remains popular in congested cities like Rome due to its efficiency in navigating traffic. However, safety concerns are a major deterrent, underscoring the need for enhanced safety regulations and alternative transport options.

The data analysis (Figure 10) reveals that in average car users would need to transfer an average of three times if they switched to PT, indicating inefficiencies in the network. Improving direct routes and reducing transfer requirements would enhance PT competitiveness with private vehicles. PT affordability, reliability, and accessibility are key to increasing ridership. Cost elasticity results suggest that fare reductions or subsidies would significantly boost public transport use. Flat-rate fares and integration with bike-sharing services improve connectivity and first- and last-mile solutions. Increasing service frequencies, providing real-time tracking, and reducing transfer requirements are crucial for improving public transport competitiveness against private vehicles.

Walking and cycling, while sustainable, are limited by travel time concerns, as active modes are mainly viable for short distances (around 5 km for cyclists and 2 km for pedestrians based on Figure 10). Expanding protected bike lanes and pedestrianized streets, developing walkable neighborhoods following the 15-minute city model, and encouraging employer support for active commuting can increase adoption. Community-based initiatives like gamification strategies and "walk/bike to work" challenges can further encourage behavior change toward active mobility.

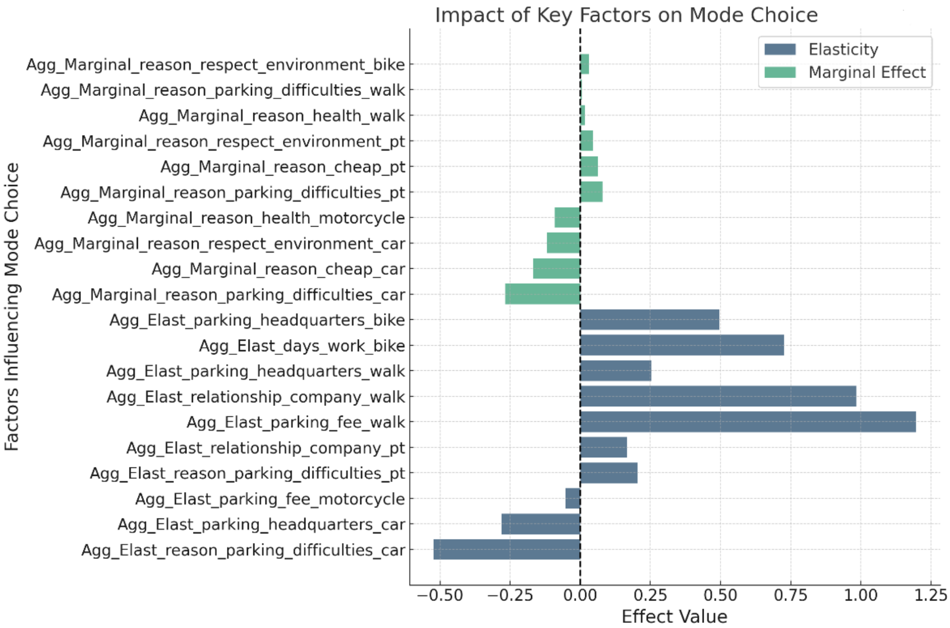


Figure 9: Elasticities (blue) and marginal effects (green) of key factors.

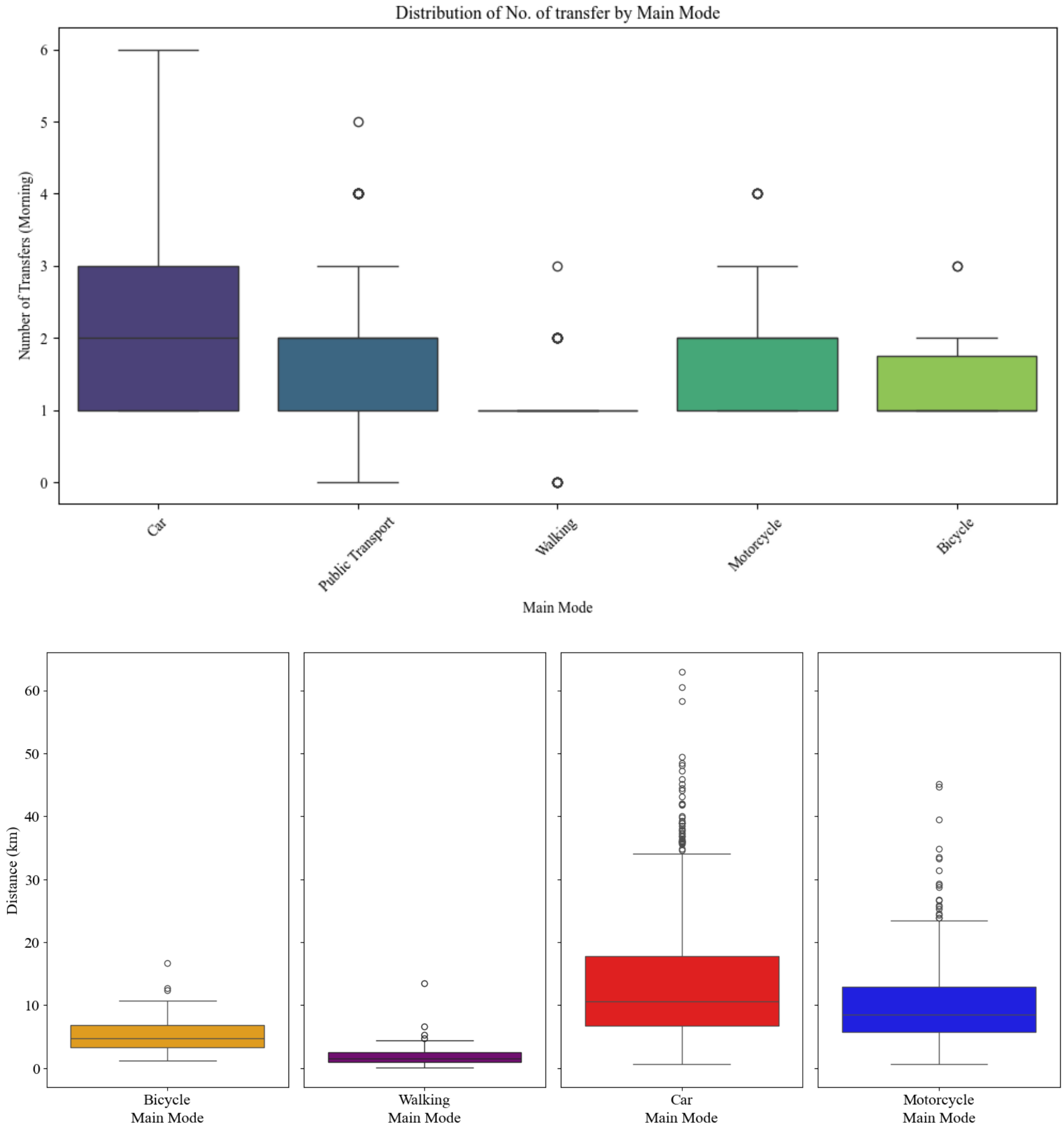


Figure 10: The distribution of No. of transfers (top) and travel distances (bottom) for each mode.

4. CONCLUSIONS

This study compares NN and MNL models using survey data from Rome employees. While the NN model achieves slightly higher accuracy, the difference is not statistically significant. The MNL model, despite its lower accuracy, provides valuable interpretability, making it a viable choice for policy applications.

The results highlight critical transportation challenges in Rome, including high car dependency, inefficient public transport connectivity, limited cycling and pedestrian infrastructure, and safety concerns for non-motorized transport users. Addressing these issues requires targeted interventions to improve mobility options and encourage sustainable transport choices. This study provides some policies to answer this problem, offering insights that can inform transportation strategies aimed at reducing car dependency and promoting sustainable mobility solutions in Rome and other cities facing similar challenges.

REFERENCES

Ben-Akiva, Moshe, and Steven R. Lerman. 1985. *Discrete Choice Analysis*. Cambridge, MA: MIT Press.

Bierlaire, Michel. 2025. “Biogeme: A Free Software for Discrete Choice Modeling.” 2025. https://biogeme.epfl.ch/.

Eldafrawi, Mohamed, Ken Koshy Varghese, Marzieh Afsari, Mahnaz Babapourdijojin, and Guido Gentile. 2024. “Predictive Analytics for Road Traffic Accidents: Exploring Severity through Conformal Prediction.” In . Washington DC, USA.

García-García, José Carlos, Ricardo García-Ródenas, Julio Alberto López-Gómez, and José Ángel Martín-Baos. 2022. “A Comparative Study of Machine Learning, Deep Neural Networks and Random Utility Maximization Models for Travel Mode Choice Modelling.” *24th Euro Working Group on Transportation Meeting* 62 (January):374–82. https://doi.org/10.1016/j.trpro.2022.02.047.

Hillel, Tim, Michel Bierlaire, Mohammed Z.E.B. Elshafie, and Ying Jin. 2021. “A Systematic Review of Machine Learning Classification Methodologies for Modelling Passenger Mode Choice.” *Journal of Choice Modelling* 38 (March):100221. https://doi.org/10.1016/j.jocm.2020.100221.

M. Afsari, M. Dastmard, L. M. Bresciani Miristice, and G. Gentile. 2024. “Utilizing P-Median and Machine Learning for Bike-Sharing Demand Prediction.” In *2024 IEEE International Conference on Environment and Electrical Engineering and 2024 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, 1–5. https://doi.org/10.1109/EEEIC/ICPSEurope61470.2024.10751398.

Martín-Baos, José Ángel, Julio Alberto López-Gómez, Luis Rodriguez-Benitez, Tim Hillel, and Ricardo García-Ródenas. 2023. “A Prediction and Behavioural Analysis of Machine Learning Methods for Modelling Travel Mode Choice.” *Transportation Research Part C: Emerging Technologies* 156 (November):104318. https://doi.org/10.1016/j.trc.2023.104318.

Rezaei, Shahrbanoo, Anahita Khojandi, Antora Mohsena Haque, Candace Brakewood, Mingzhou Jin, and Christopher Cherry. 2021. “Performance Evaluation of Mode Choice Models under Balanced and Imbalanced Data Assumptions.” *Transportation Letters* 14 (8): 920–32. https://doi.org/10.1080/19427867.2021.1955567.

Wener, Richard E., and Gary W. Evans. 2011. “Comparing Stress of Car and Train Commuters.” *Transportation Research Part F: Traffic Psychology and Behaviour* 14 (2): 111–16. https://doi.org/10.1016/j.trf.2010.11.008.

Xiong, Jingwen, Lunhui Xu, Zhuoyan Wei, Pan Wu, Qianwen Li, and Mingyang Pei. 2024. “Identifying, Analyzing, and Forecasting Commuting Patterns in Urban Public Transportation: A Review.” *Expert Systems with Applications* 249 (September):123646. https://doi.org/10.1016/j.eswa.2024.123646.