From Spontaneity to Planning: Understanding Long-Distance Travelers' Mode Choice Preferences for BlaBla Carpooling, Bus, and Train in Central Europe

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ARTICLE INFO

Keywords:
Long-distance travel
BlaBla carpooling
Multi-level mixed-effect logistic regression
Prague

ABSTRACT

This study investigates the mode choice preferences of long-distance travelers in Central Europe, focusing on BlaBlaCar carpooling, trains, and buses. Utilizing three months of operational data from BlaBlaCar, a multilevel mixed-effect logistic regression model was applied to examine mode choice behavior under 1-day and 10-day advance booking scenarios. The results reveal that travelers prefer buses for shorter trips, while trains are favored for longer journeys, with carpooling being a less frequent choice. Carpooling is most popular for spontaneous, long-distance travel, whereas advanced bookings are less likely to include this option. Additionally, district-level demographics significantly influence preferences: older travelers and pedestrians tend to choose buses, while individuals without formal education show a marked preference for buses over carpooling, especially when planning trips in advance. These findings underscore the potential of BlaBlaCar carpooling to complement existing public transport systems, thereby enhancing urban mobility and supporting the development of sustainable, multimodal transportation networks.

1. Introduction

The optimization of long-distance travel has become a strategic priority for policymakers, urban planners, and transportation providers globally. One of the primary challenges confronting modern transportation systems is the persistently low occupancy rate of private vehicles, with most trips comprising only one or two passengers. This trend exacerbates traffic congestion, increases fuel consumption, and heightens carbon emissions, contributing to environmental degradation and straining urban infrastructure, as highlighted by U.S. Bureau of Transportation Statistics (2023), and Eurostat (2024). Despite the capacity of most vehicles to carry more passengers, widespread underutilization continues across both the United States and the European Union, revealing deep-rooted inefficiencies in resource management and urban mobility. Addressing these issues is essential to fostering transportation systems that are sustainable, efficient, and resilient.

Carpooling has emerged as a viable strategy to address these inefficiencies by optimizing vehicle occupancy and promoting environmental sustainability. With over 100 million users across 22 countries, BlaBlaCar exemplifies how digital solutions can reshape intercity travel, reducing search and transaction costs and making carpooling a practical option for long-distance journeys (BlaBlaCar, 2022). Carpooling's potential to reduce vehicle miles traveled and lower emissions aligns with broader environmental goals. Research by Aguiléra and Pigalle (2021) and Krawiec (2024) demonstrates that higher vehicle occupancy rates can significantly decrease urban pollution and mitigate traffic congestion. The platform's expansion into multimodal transport, including bus services and planned train bookings, underscores its ambition to become a comprehensive mobility provider (Laroche and Blayac, 2020). However, the success of this model hinges on a nuanced understanding of user preferences, including how demographic factors and trip-specific conditions influence mode choice between carpooling and other transportation options.

Current literature on carpooling provides important insights into the motivations and barriers associated with shared travel. Research indicates that economic savings, environmental consciousness, and social benefits are primary drivers of carpooling adoption (Monchambert, 2020; Shaheen, Stocker and Mundler, 2017). Studies from France, Spain, and other European countries reveal that carpooling appeals to various users, including students, budget-conscious young travelers, and environmentally aware individuals. However, much of this research is region-specific and lacks comparative perspectives that consider differences in public transportation infrastructure and local travel behaviors. For instance, work by Hinojo, García-Mariñoso and Suárez (2024) and Cellina, Derboni, Giuffrida, Tomic and Hoerler (2024) highlights the importance of trust and ride availability for last-minute travelers but does not sufficiently explore how these factors influence decision-making in different contexts.

Traveler preferences are shaped by multiple factors, such as fare sensitivity, travel distance, time constraints, and psychological considerations Lanzini and Khan (2017); Vij, Carrel and Walker (2013). A critical gap exists in understanding how booking timelines, specifically, last-minute versus planned bookings, impact mode choice decisions. Evidence suggests that travel urgency influences decision-making, with last-minute travelers prioritizing immediate

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availability and convenience, while those who plan in advance often emphasize cost and comfort (Mars, Ruiz and Arroyo, 2018; Ferrer and Ruiz, 2014).

A key aspect of predicting mode choice behavior among long-distance travelers is ticket availability. Last-minute travelers tend to opt for readily available options, while those planning ahead prioritize cost and travel time (Vij et al., 2013; Mars et al., 2018). Examining booking data from 1-day and 10-day advance timelines can illuminate how preferences for carpooling, bus, and train travel vary in urban contexts like Prague. Additionally, the timing and urgency of a trip influence mode choice, with travelers exhibiting distinct preferences based on the reliability and availability of transport options as departure approaches (Ferrer and Ruiz, 2014; Wakabayashi, Asaoka, Iida and Kameda, 2003).

This study aims to bridge these research gaps by analyzing long-distance mode choice behavior among travelers in Prague, focusing on BlaBlaCar carpooling, trains, and buses. Prague's extensive public transportation network—comprising trains, buses, and metro services—makes it an ideal case for studying mode choice behavior. The research employs a multi-level mixed-effect logistic regression model to examine the influence of variables such as fare, travel distance, and trip duration on travelers' decisions. The model incorporates booking timelines (1-day versus 10-day advance bookings) to assess the effects of spontaneity and planning. District-level demographic data—including age distribution, educational background, and primary transport mode usage—will be integrated to explore their impact on travel preferences. This multi-level approach allows for a detailed understanding of how individual and district-level factors interact to shape mode choice behavior, capturing the heterogeneity of preferences across different population segments. Insights from this study may serve as a blueprint for other metropolitan areas aiming to integrate carpooling and shared mobility into their transportation networks more effectively.

By examining booking timelines and demographic characteristics, this study enhances traditional mode choice models to reflect real-world scenarios where travel decisions are shaped by personal and contextual variables. The findings aim not only to deepen the understanding of carpooling's role within multimodal transport systems but also to provide practical guidance for policymakers, urban planners, and transportation operators seeking to foster more efficient and eco-friendly urban travel solutions.

2. Methdology

2.1. Data

2.1.1. BlaBla Carpooling Operational data

This research uses a detailed dataset of BlaBlaCar's intercity travel routes across central Europe, focusing on pricing and route information. The dataset includes four modes of transport—airplane, train, bus, and carpooling—and provides information such as country, travel direction, departure and arrival times, travel date, origin and destination stations, service provider, ticket prices, availability, and seat occupancy. The dataset also captures essential trip characteristics, such as total distance, duration, speed, and economic factors like total trip cost, cost per kilometer, and cost per hour. To focus the analysis on road transport mode choice, only trips departing from Prague were selected, excluding airplane trips. This approach highlights the competitive and complementary dynamics among carpooling, train, and bus routes. It enables a closer examination of how factors like price, distance, duration, and booking lead time influence travelers' choices. This refined dataset provides valuable insights into intermodal competition and the role of carpooling within European urban mobility, especially within Prague's extensive transport network.

Table 1 reveals insightful trends regarding mode preferences across different booking periods. The overall distribution indicates that train usage dominates, comprising approximately 54%, followed by bus usage at 40.4%, and carpooling at 5.7%. When examining 1-day advance ticket bookings, there is a slight shift: train usage decreases slightly to 52.3%, and bus usage accounts for 39.2%, while carpooling rises to 8.5%. This increase in carpooling may indicate that closer-to-departure bookings are associated with more flexible, last-minute travel arrangements, where shared rides become more attractive due to convenience or availability. In contrast, the 10-day advance ticket booking shows a distinct pattern where train usage climbs to 55.7% and bus usage increases to 41.6%, while carpooling drops significantly to 2.7%. This distribution reflects a higher reliance on public transit options for planned, longer-term travel. The reduced share of carpooling suggests that when travelers plan in advance, they opt for more reliable and structured transport modes like trains and buses.

2.1.2. Prague's Municipal Districts Data

To analyze the impact of demographic and socio-economic factors on mode choice behavior, district-level data from Prague were incorporated. This dataset includes variables grouped into four primary domains: demographics, major means of transport, educational background, and economic conditions. Demographic data classify the population into three age groups—Young (1-18), Middle-Aged (18-65), and Older Adults (65 and above)—each reflecting distinct mobility needs. Primary modes of transport data shed light on how local travel habits shape long-distance travel choices. Variables such as the proportion of residents who primarily bicycle, walk, or use personal vehicles indicate environmental awareness or car dependency, influencing the probability of selecting shared transport. The prevalence of public transport use suggests potential competition with carpooling services.

The dataset also captures educational background, revealing contrasting user behavior between university students and individuals without formal education. Economic

Table 1
Distribution of Price, Distance, Time Duration, and Mode Share by Booking Type

Booking Type	Metric	Bus	Carpooling	Train
Overall	Average Price	15.80	9.59	12.06
	Average Distance (km)	296.45	247.45	235.27
	Average Time Duration (hrs)	4.43	3.09	2.76
	Mode Share (%)	40.35%	5.69%	53.96%
1-Day Advance	Average Price	15.98	9.52	12.67
	Average Distance (km)	295.40	246.15	234.59
	Average Time Duration (hrs)	4.40	3.07	2.76
	Mode Share (%)	39.16%	8.55%	52.29%
10-Day Advance	Average Price	15.62	9.83	11.47
	Average Distance (km)	297.49	251.75	235.94
	Average Time Duration (hrs)	4.45	3.15	2.77
	Mode Share (%)	41.60%	2.69%	55.71%

Table 2
Summary Statistics of Variables

Level	Category	Variables	Mean	Standard Deviation	Min	Max
		Dependent Variables				
	Demand Attributes	Total number of trips	1,128	952	0	29,338
		Total trips with 1-day advance booking	576	452	0	15,000
		Total trips with 10-day advance booking	651	501	0	14,338
		Independent Variables				
Trip	Trip Characteristics	Price	13	11	1	119
		Distance	261	142	91	705
		Travel duration	3	2	1	14
		Speed	83	19	11	143
District	Demographics	Middle age	42,447	16,832	1,659	5,330
		Old age	11,684	7,256	307	7,852
		Young age	8,338	4,312	498	7,775
	Means of Transport	Bicycling	369	160	8	734
		Walking	2,583	436	20	3,859
		Personal Car	4,753	2,924	437	12,616
		Municipal public transport	12,713	6,349	259	26,094
	Education	University	19,505	6,523	616	37,324
		Without education	204	93	4	415
	Economic	Working students	17,181	8,168	669	8,059
		Employees	19,505	6,523	616	7,324

variables, such as the number of working students and employed individuals, were considered to assess how cost sensitivity and employment status affect mode choice. Integrating these district-level variables provides comprehensive insights into how demographic and socio-economic factors shape the use of carpooling, especially under different ticket availability scenarios.

Table 2 presents descriptive summary statistics for the key variables associated with BlaBlaCar pooling demand and district-level characteristics analyzed in this study. The total number of trips per district averages 1,128, with a considerable range extending up to 29,338 trips. These trips were further classified into two categories based on booking lead time to establish the two dependent variables, calculated separately through MMLR. For 1-day advance bookings, the average number of trips is 576, while for 10-day advance bookings, the average is slightly higher at 651, reflecting a tendency toward short-term planning.

The independent variables consist of two levels: trip-level and district-level, with the former showing mean values per trip across the dataset. Summary statistics indicate that average trip prices stand at 13 euros, with distances averaging 261 kilometers and trip durations around 3 hours.

At the district level, four categories significantly influence BlaBlaCar users' mode choice: demographics (middle-aged population dominates at 42,447 per district), transport modes (public transport is widely used, while cycling is less common), educational attainment (university-educated residents average 19,505, with lower education linked to reduced carpooling adoption), and economic status (working students show a preference for cost-effective, tech-driven options). These factors collectively shape carpooling demand. Overall, these metrics are expected to capture the demographic, economic, and mobility factors influencing carpooling demand.

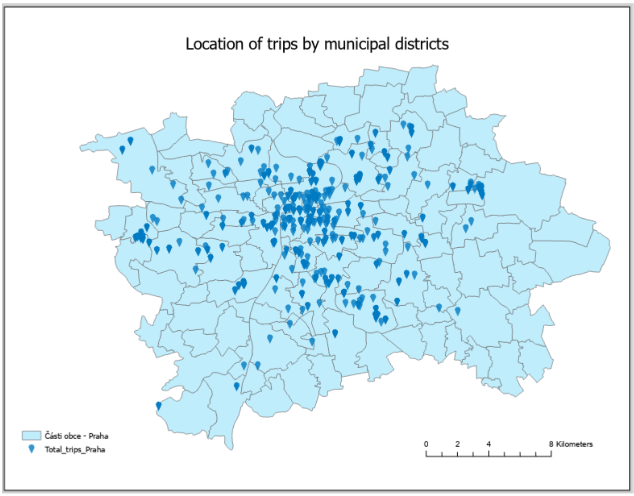

Figure 1: Loaction of trips by Pragu's Municipal Districts

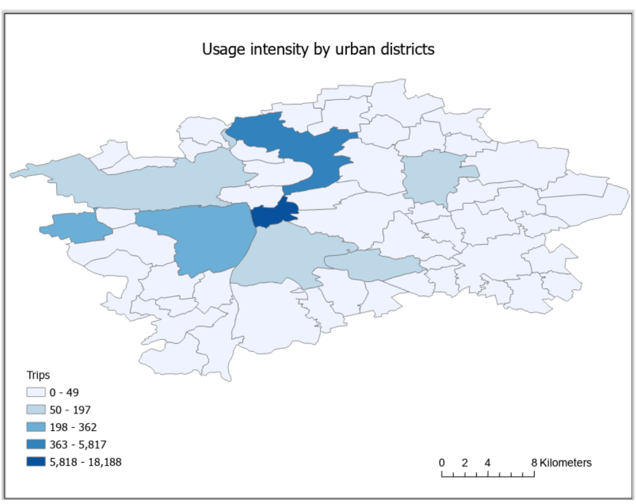

Figure 2: Distribution of Demand by Pragu's Municipal Districts

2.2. The Multilevel Multinomial Logit Model

2.2.1. The GLM Formulation

Multinomial choice models, commonly called "discrete choice models" in econometrics (McFadden, 1972; Train, 2009), are widely used across fields like economics, sociology, and health sciences to analyze choices between multiple distinct options. These models help reveal factors influencing individual decisions, such as transportation modes, product preferences, or medical treatments. Multinomial choice models are further extended to incorporate multilevel or clustered responses, which account for the existing degree of dependence within these clusters (Skrondal and Rabe-Hesketh, 2004; Hedeker, 2003), which accounts for the existing degree of dependence within these clusters (Hedeker, 2003). A study by Hartzel, Agresti and Caffo (2001) emphasized that ignoring this dependence in the data may lead to a loss of within-cluster information regarding intraclass correlations. Despite of the extension of these models practical applications remain relatively uncommon. In this paper, we explore the multilevel multinomial logit model—a mixed Generalized Linear Model (GLM) (McCullagh, 2019)—which incorporates both linear predictors and a multinomial logit link.

We define the linear predictor for each response category $m = 1, 2, \ldots, M$, cluster j, and subject i as:

$$\eta_{ij}^{(m)} = \alpha^{(m)} + \beta^{(m)\prime} x_{ij} + \xi_j^{(m)} + \delta_{ij}^{(m)} \tag{1}$$

The corresponding multinomial logit link is:

$$P(Y_{ij} = m \mid x_{ij}, \xi_j, \delta_{ij}) = \frac{\exp\{\eta_{ij}^{(m)}\}}{1 + \sum_{l=2}^{M} \exp\{\eta_{ij}^{(l)}\}} \tag{2}$$

where Y_{ij} is the response variable for subject i in district j, taking values from a set of four differnt mode categories $\{1, 2, \ldots, M\}$. Here, $m = 1$ is the reference category that is train, and the probabilities are defined relative to it.

This model assumes independent random effects at different levels. Specifically:

- $\xi_j' = (\xi_j^{(2)}, \ldots, \xi_j^{(M)})' \sim \mathcal{N}(0, \Sigma_\xi)$representing unobserved heterogeneity at the district level.
- $\delta_{ij}' = (\delta_{ij}^{(2)}, \ldots, \delta_{ij}^{(M)})' \sim \mathcal{N}(0, \Sigma_\delta)$representing scenario-specific errors.

In practice, the parameters of the district-level covariance matrix Σ_ξ are identifiable, while those of Σ_δ may face empirical challenges. In Section 4, we demonstrate that the subject-level covariance parameters are not empirically identified and are therefore omitted from our application. Nevertheless, we include them in this theoretical section to showcase the full flexibility of the model.

One of the key features of this model is its treatment of the Independence from Irrelevant Alternatives (IIA) property. The odds ratio between any two chosen modes m and l for a given scenario i and cluster j depends only on the corresponding linear predictors:

$$\frac{P(Y_{ij} = m \mid x_{ij}, \xi_j, \delta_{ij})}{P(Y_{ij} = l \mid x_{ij}, \xi_j, \delta_{ij})} = \exp\{\eta_{ij}^{(m)} - \eta_{ij}^{(l)}\} \tag{3}$$

This conditionally satisfies the IIA assumption. However, because IIA holds only conditionally on covariates and random errors, the introduction of random terms in the

Table 3
Results of MMLR models for 1-day and 10-day advance bookings.

Category	Variables	1 Day Advance Booking		10 Days Advance Booking	
		Bus	Carpooling	Bus	Carpooling
BlaBla Carpooling characteristics	Price	0.0143***	-0.1126***	0.0294***	-0.0714***
	Distance	-0.0085***	0.0039***	-0.0093***	0.0054***
	Time duration	0.8851***	0.1589*	0.8864***	-0.1070
Demographics	Middle age	-0.0035	0.0002	-0.0022	0.0019**
	Old age	0.0014*	-0.0011†	0.0011*	-0.0014**
Mean of Transport	Cycling	-0.0131	-0.0087	-0.0127	-0.0014
	Walking	-0.0163**	-0.0158***	-0.0106***	-0.0116***
	Personal Car	-0.0065***	-0.0054***	-0.0049**	-0.0042**
	Municipal public transport	-0.0035*	-0.0048***	-0.0017†	-0.0039***
Education	University	-0.0021	-0.0026†	-0.0001	-0.0005
	No education	0.0478*	-0.0788*	0.0580	-0.0522**
Economic	Working students	0.0139*	0.0080†	0.0025	-0.0019
	Employees	0.0066	0.0042	0.0038	0.0007
Model fit parameters	Variance	0.030	-	0.201	-
	Log likelihood	-	-5607.759	-	-4252.477

***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.1

predictors helps relax the IIA assumption, increasing model flexibility.

Finally, the likelihood of the model can be written as:

$$L(\theta) = \prod_{j=1}^{J} \prod_{i=1}^{n_j} \int \left\{ \int P(Y_{ij} \mid x_{ij}, \xi_j, \delta_{ij}) f(\delta_{ij}) d\delta_{ij} \right\} \times f(\xi_j) d\xi_j \quad (4)$$

Here, the likelihood involves integrals over the random effects, which do not have closed-form solutions. We estimate the parameters using adaptive Gaussian quadrature, as implemented by the `gllamm` command in Stata (Rabe-Hesketh, Skrondal and Pickles, 2004). This method effectively approximates the required integrals, ensuring accurate parameter estimation.

3. Results

The analysis of the Multilevel Multinomial Logistic Regression (MMLR) models for 1-day and 10-day advance booking scenarios is outlined in Table 3. This table reports the estimated coefficients, statistical significance, and key model fit metrics such as AIC and BIC. Both models display strong predictive capability, as evidenced by lower AIC and BIC values when compared to simpler multinomial logistic regression models. The random intercept standard deviations for the 1-day and 10-day models, at 0.174 and 0.449 respectively, indicate that 17% of the variance in mode choice for 1-day bookings is attributed to between-district variations, increasing to 45% in the 10-day scenario. This shift underscores the greater influence of regional demographics in longer-term planning.

The 1-day advance booking model highlights significant relationships between trip characteristics and mode choice. A 1 fare increase raises bus selection odds by 1.4% but reduces carpooling by 10.6%, indicating heightened price sensitivity for spontaneous travel. Each additional kilometer decreases bus preference by 0.8% but increases carpooling by 0.39%. Longer trip durations significantly enhance the appeal of both buses (142%) and carpooling (17%).

Demographic factors further influence choices. Older users show a slight preference for buses, while middle-aged users exhibit no notable impact. Walking and public transport usage reduce the likelihood of selecting both buses and carpooling, favoring train travel. Education levels play a role: university-educated individuals favor trains, while those without formal education prefer buses over carpooling. Economically, working students lean toward cost-effective options like buses (1.39%) and, to a lesser extent, carpooling (0.8%), while employed individuals show stable preferences. These trends underscore the complex interplay of trip, demographic, and economic factors in mode selection.

3.1. 10-day advance booking model

The 10-day advance booking model reveals greater price sensitivity for buses, with a 1 increase raising selection odds by 2.94% and reducing carpooling by 7.14%. Distance decreases bus preference by 0.93% per kilometer but increases carpooling by 0.54%, showing its appeal for longer trips. Unlike the 1-day model, trip duration does not significantly affect carpooling.

Walking and personal car use reduce preferences for both bus and carpooling, favoring trains. Older users maintain a slight preference for buses, while middle-aged and younger demographics show no significant impact. Individuals without formal education strongly favor buses (5.22%) over carpooling (-5.22%), reflecting accessibility factors. Working students prefer buses (2.5%) but show no significant shift toward carpooling. The model's higher variance and better

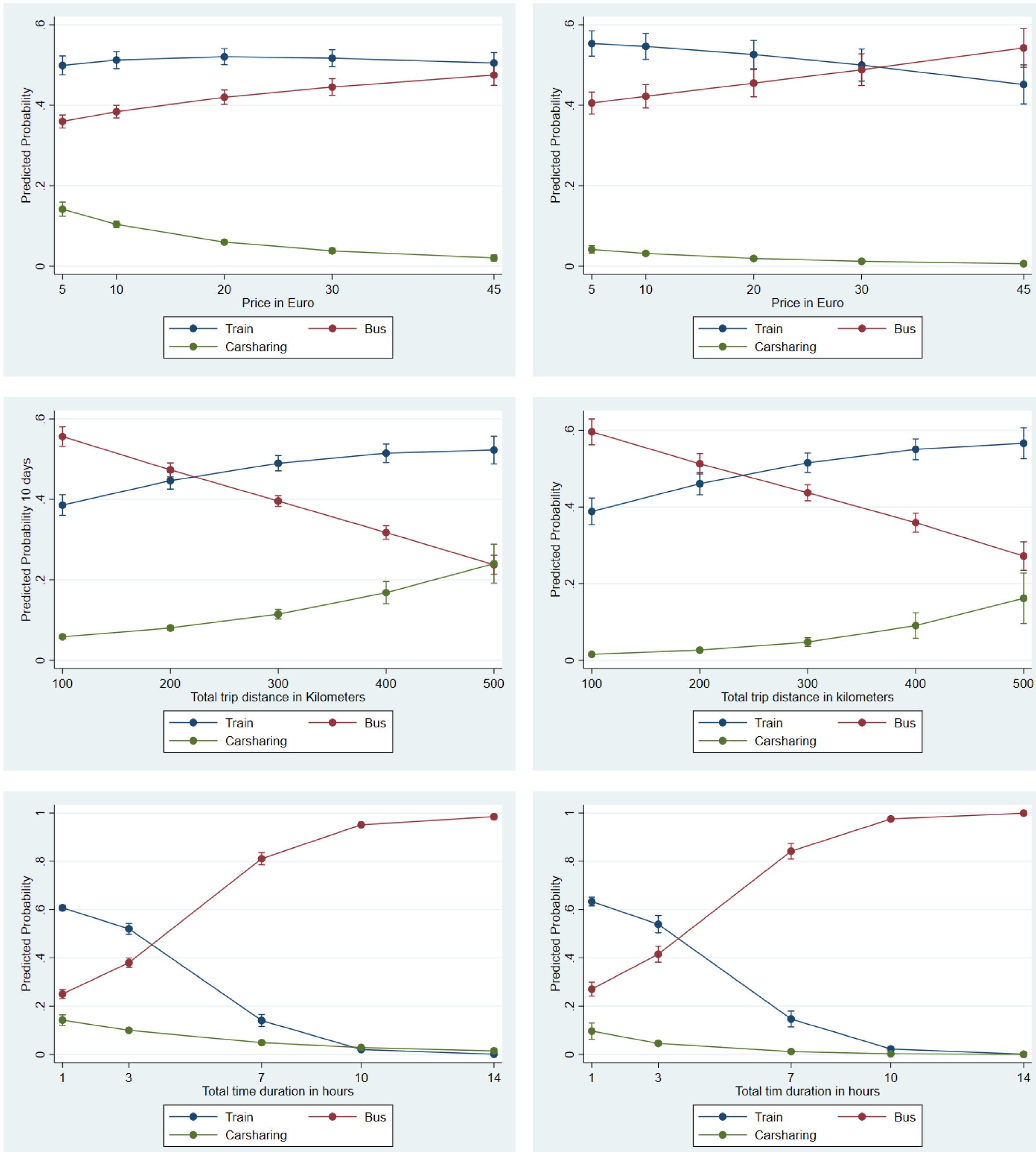

Figure 3: Predicted marginal probabilities of mode choices (Train, Bus, Carpooling) across trip characteristics, with 95% Confidence Intervals

log-likelihood compared to the 1-day scenario highlight carpooling's complementary role in planned multimodal systems.

3.2. The Predictive Marginal Probabilities

Figure 3 shows predictive probabilities for train, bus, and carpooling. In the 1-day model, buses dominate short distances, with trains preferred for longer trips, while carpooling gains appeal for extended journeys. In the 10-day model, trains dominate long distances, and buses remain strong for short trips, with carpooling showing limited appeal.

Price sensitivity is evident, with trains and buses favored at lower prices, while rising costs reduce bus use and leave carpooling minimally affected. Duration analysis highlights trains as reliable for long trips, with carpooling suiting spontaneous travel but playing a secondary role in planned scenarios. These findings confirm carpooling's complementary role in multimodal systems, particularly for last-minute travel.

4. Discussion

This study examines long-distance mode preferences in Prague, focusing on BlaBlaCar, buses, and trains. Using a multilevel logistic model, key factors like booking timelines, fares, distances, and demographics were analyzed.

Older adults prefer buses, emphasizing accessibility, while younger users, especially students, favor carpooling due to flexibility and affordability. Trains dominate longer trips for their reliability and efficiency. Carpooling thrives in last-minute bookings but sees reduced use in planned travel due to trust and scheduling preferences.

Fare sensitivity plays a major role, with budget-conscious travelers opting for cost-effective modes. Those without formal education lean toward buses over carpooling, while digitally fluent users prefer tech-integrated options. Economic factors show working students favor shared travel, while employed individuals exhibit stable preferences.

Policy recommendations include integrating carpooling into public transit, dynamic pricing, and user-friendly platforms to enhance urban mobility. Carpooling complements transit by addressing gaps, particularly for spontaneous, mid-distance trips, promoting sustainable practices.

References

Aguiléra, A., Pigalle, E., 2021. The future and sustainability of carpooling practices. an identification of research challenges. Sustainability 13, 11824.

BlaBlaCar, 2022. 2022 impact report: Declaration of extra-financial performance. URL: https://www.blablacar.com. blaBlaCar's intermodal approach towards sustainable shared mobility.

Cellina, F., Derboni, M., Giuffrida, V., Tomic, U., Hoerler, R., 2024. Trust me if you can: Practical challenges affecting the integration of carpooling in mobility-as-a-service platforms. Travel Behaviour and Society 37, 100832.

Eurostat, 2024. Transport statistics. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php/Transport. european Commission.

Ferrer, S., Ruiz, T., 2014. Factors influencing the travel scheduling of driving trips of habitual car users. Transportation Research Record 2412, 1–9. doi:10.3141/2412-12.

Hartzel, J., Agresti, A., Caffo, B., 2001. Multinomial logit random effects models. Statistical Modelling 1, 81–102.

Hedeker, D., 2003. A mixed-effects multinomial logistic regression model. Statistics in medicine 22, 1433–1446.

Hinojo, P., García-Mariñoso, B., Suárez, D., 2024. On actual carpooling behaviour: a nationwide study in spain. Applied Economics , 1–11.

Krawiec, W., 2024. Carpooling and natural resource protection: shared transport users' perspective. Zeszyty Naukowe. Organizacja i Zarządzanie/Politechnika Śląska .

Lanzini, P., Khan, S., 2017. Shedding light on the psychological and behavioral determinants of travel mode choice: A meta-analysis. Transportation Research Part F: Traffic Psychology and Behaviour 47, 13–27. doi:10.1016/J.TRF.2017.04.020.

Laroche, F., Blayac, T., 2020. Intermodal competition on the long-distance passenger market: substitutability or complementarity? evidence from france. hEART 2020 Symposium URL: https://heart2020.com.

Mars, L., Ruiz, T., Arroyo, R., 2018. Identification of determinants for rescheduling travel mode choice and transportation policies to reduce car use in urban areas. International Journal of Sustainable Transportation 13, 433–447. doi:10.1080/15568318.2017.1416432.

McCullagh, P., 2019. Generalized linear models. Routledge.

McFadden, D., 1972. Conditional logit analysis of qualitative choice behavior .

Monchambert, G., 2020. Why do (or don't) people carpool for long-distance trips? a discrete choice experiment in france. Transportation Research Part A: Policy and Practice 132, 911–931. doi:10.1016/j.tra.2019.12.033.

Rabe-Hesketh, S., Skrondal, A., Pickles, A., 2004. Generalized multilevel structural equation modeling. Psychometrika 69, 167–190.

Shaheen, S., Stocker, A., Mundler, M., 2017. Online and app-based carpooling in France: Analyzing users and practices—A study of BlaBlaCar. Springer.

Skrondal, A., Rabe-Hesketh, S., 2004. Generalized Latent Variable Modeling. Chapman Hall/CRC, London.

Train, K.E., 2009. Discrete choice methods with simulation. Cambridge university press.

U.S. Bureau of Transportation Statistics, 2023. Transportation statistics annual report. URL: https://www.bts.gov/tsar. u.S. Department of Transportation.

Vij, A., Carrel, A.L., Walker, J.L., 2013. Incorporating the influence of latent modal preferences on travel mode choice behavior. Transportation Research Part A: Policy and Practice 54, 76–92. doi:10.1016/J.TRA.2013.07.008.

Wakabayashi, H., Asaoka, K., Iida, Y., Kameda, H., 2003. Mode choice model with travel time reliability and commuters' travel behavior before/after a major public transportation service closure. International Journal of Transportation 4, 123–137. doi:10.1108/9781786359544-010.