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Exploring peer-to-peer paid carpooling in Bogotá: A path to sustainable shared mobility

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ABSTRACT

Carpooling is a sustainable transportation alternative that allows users with similar destinations to share private vehicles, contributing to reductions in energy consumption, pollutant emissions, and traffic congestion. While not a comprehensive solution, carpooling can lower private car use and increase vehicle occupancy rates. However, most carpooling initiatives have been limited in scope, often operating on a small scale or within corporate frameworks, restricting their potential for widespread adoption. In Latin America, where ride-hailing services are popular despite regulatory issues, carpooling remains uncommon. In Bogotá, an exception is the informal service called "Wheels," which operates through WhatsApp groups to coordinate rides, focusing on university communities. This service quickly became a preferred mode of transport for students, faculty, and staff. This study aims to identify the factors driving the success of this informal initiative. A survey of 470 university community members was conducted, incorporating a discrete choice experiment to evaluate the attributes influencing their stated likelihood of use. Analytical methods included multiple correspondence analysis, logit models, and machine learning techniques. Our findings reveal that the adoption of carpooling is significantly influenced by price sensitivity, safety perceptions (particularly among women), reluctance to share rides with strangers, and demographic factors such as age and socioeconomic status. These insights offer valuable guidance for enhancing the appeal and scalability of carpooling as a door-to-door, reliable transportation alternative, particularly in similar sociocultural contexts as our case study.

1. Introduction

Despite the City of Bogotá's efforts to improve public transportation, it is still not the preferred option for daily commutes. With a population of 7.89 million and over 13 million daily trips (DANE, 2024), Bogotá exhibits a significant reliance on private vehicles, with 15% of trips made by car, surpassing public transport and active modes (Secretaría Distrital de Movilidad, 2019). Recent data from the 2023 Bogotá-Region Mobility Survey provide a more comprehensive view of these dynamics. Public transport represents 34.7% of daily trips, active modes (walking and cycling) account for approximately 35%, and private motorized transport (cars and motorcycles) makes up around 21%. Together, public and active modes thus represent nearly two-thirds of daily mobility in the city, highlighting the persistent yet limited role of private vehicles in overall travel behavior and underscoring the importance of promoting shared mobility solutions such as carpooling. This preference for private cars is driven by perceptions of comfort and flexibility, despite their substantial economic, environmental, and social costs (Rohács and Rohács, 2020). The resulting externalities include traffic congestion, estimated to cause annual economic losses of 5 trillion Colombian pesos (Banco Mundial, 2020); traffic accidents, with 5533 injuries and 579 fatalities in 2024 (ANSV, 2024); and significant contributions to CO_2 emissions, accounting for 43% of the city's total (Seguel et al., 2022). While the Integrated Public Transport System (SITP), facilitates a considerable share of public transport trips, users perceive deficiencies in service frequency, affordability, safety, and

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comfort (Rodriguez-Valencia et al., 2023; Toro-González et al., 2020).

Shared mobility has emerged as a promising alternative to mitigate these externalities, with the potential to reshape urban transport systems (Castellanos et al., 2022). Carpooling, a modality within ridesharing, is particularly relevant for managing private vehicle travel demand by optimizing vehicle occupancy (Si et al., 2023). Defined as a non-commercial arrangement where drivers share trips with non-dependent passengers (Amirkiaee and Evangelopoulos, 2018), carpooling often fosters group identity through shared destinations, such as workplaces or educational institutions (Cellina et al., 2024). In the Global South, carpooling frequently adopts an "open" format characterized by flexibility and spontaneity, leveraging social networks and messaging applications for real-time ride matching. This stands in contrast to the more "structured" systems prevalent in the Global North, which are defined by an organized and regular approach typically implemented within corporate, institutional, or municipal contexts. Such systems are governed by established rules, fixed routes, and recurring users (Furuhata et al., 2013; Amirkiaee and Evangelopoulos, 2018).

Unlike on-demand services like Uber, DIDI, and Cabify, or dynamic ridesharing, open carpooling uses social networks and direct messaging apps to facilitate real-time matching of passengers and drivers (Agatz et al., 2012; Chan and Shaheen, 2012). Moreover, open carpooling relies on factors like perceived sharing authenticity, grassroots engagement, sharing orientation and the perception of modernity and trendiness (Guyader et al., 2023). It has also been shown to positively influence safe driving behavior, as carpooling drivers tend to reduce episodes of speeding and mobile phone use compared to other drivers (Bastos et al., 2021).

In 2022, Bogotá led the world traffic ranking due to severe congestion, with drivers losing 132 h annually in traffic jams. In 2023, there was a slight improvement, with a reduction to 117 h lost and an average time of 25 min for every 10-kilometer journey (TomTom Traffic Index, 2023). Thereby, Bogotá exemplifies the challenges of rapid urbanization, spatial segregation, and rising motorization rates. These conditions have spurred interest in carpooling solutions like "Wheels", a local initiative launched in 2010 at the Universidad de Los Andes. This open-source service connects drivers and passengers through WhatsApp group messages, facilitating shared trips and costs. This study specifically investigates the factors influencing the stated likelihood of carpooling adoption in this context, using a stated preferences experiment to model user decisions (Simancas et al., 2024).

Despite growing interest, research on carpooling in cities of the Global South remains scarce (spatial gap). Most studies focus on the Global North, where robust infrastructure, high motorization rates, and structured mobility systems create conditions distinct from the rapid urbanization, high population density, and safety challenges observed in cities like Bogotá. These contextual differences influence the adoption and operation of carpooling, particularly in open and dynamic modalities, which are underexplored in existing literature (empirical gap) (Fleiter et al., 2010).

Furthermore, while previous studies have acknowledged economic and environmental benefits as key motivators for carpooling, critical factors such as trust within communities, driver responsibility, and user safety perceptions remain insufficiently studied (conceptual gap). This lack of understanding limits the development of strategies that address the social and psychological dynamics influencing carpooling decisions, particularly in informal systems such as "Wheels".

Additionally, traditional methodological approaches in carpooling research often rely on discrete choice models, which assume linear relationships between variables and may not fully capture the complex, non-linear interactions shaping user behavior (methodological gap). By combining multiple correspondence analysis, binomial logit models, and machine learning techniques, this study introduces a more robust approach to analyzing carpooling adoption in Bogotá's university communities.

By addressing these gaps, this research provides empirical insights that can inform urban planners and policymakers to develop data-driven strategies for promoting vehicle sharing and advancing sustainable urban mobility within similar contexts, particularly university communities in high-growth urban environments.

2. Literature review

Carpooling has been widely studied due to its potential to enhance transport efficiency and reduce environmental impact (Shaheen et al., 2012; Yu et al., 2017). By reducing vehicle kilometers traveled (VKT) carpooling helps alleviate congestion and pollution compared to other shared mobility models (Neoh et al., 2017; Shaheen and Cohen, 2019). However, the full realization of these benefits depends on factors, such as personal preferences, technological gaps and demographic characteristics (Bulteau et al., 2019).

Early studies, such as Levin (1982) at the University of Iowa, identified key user preferences for carpooling, finding that students valued familiarity and sex of the occupants, while officials prioritized schedule alignment and proximity. More recently, Ashraf Javid and Al-Khayyat (2021) used stated preference surveys, Exploratory Factor Analysis (EFA), and Structural Equation Modeling (SEM) to confirm the relevance of aforementioned factors and highlight new aspects, such as cultural influences, control of the environment inside the vehicle, social restrictions, and stress reduction at the University of Nizwa, Sultanate of Oman.

In Bogotá, studies on carpooling remain limited. Simancas et al. (2024) analyzed student carpoolers at the Universidad de Los Andes, using data from the University Travel Survey and Integrated Choice and Latent Variable (ICLV), finding that drivers are motivated by sustainability and economic incentives, while passengers, particularly women, prioritize comfort due to safety concerns. This aligns with broader findings that fear and perceived harassment in public transport affect mode choice (Orozco-Fontalvo et al., 2019; Quinones, 2020; Stark and Meschik, 2018). Despite these insights, research on carpooling in Bogotá has focused narrowly on a single university, leaving broader questions about its adoption and barriers in the city unanswered.

Economic and environmental motivations are central to carpooling adoption. Correia & Viegas (2011), using multinomial logit models applied to stated preferences in Lisbon, identified cost and time savings as key factors, while Shaheen et al. (2016) confirmed these findings in the San Francisco Bay Area, noting that environmental benefits are often secondary to economic incentives, using interviews and surveys. However, Delhomme and Gheorghiu (2016), based on a binomial logistic regression analysis of a survey in France, highlighted that individuals with strong environmental awareness, particularly women and young people, are more likely to adopt carpooling, emphasizing the diversity of motivations. Social factors also play a critical role. Sentiment analysis of Twitter data by Ciasullo et al. (2018) revealed that while users appreciate sustainability, reduced traffic, and socialization, concerns about privacy, security, and trust remain significant barriers. These findings show the complex interplay of economic, social, and perceptual factors influencing carpooling adoption.

From a methodological perspective, tools like Multiple Correspondence Analysis (MCA) have been used to identify patterns in transportation decisions, particularly when analyzing categorical data (Macharis et al., 2010; Zubaryeva et al., 2012). MCA complements discrete choice models, such as logit models, by capturing interactions between variables which are often oversimplified in traditional methods (McFadden, 1974a; Ben-Akiva and Lerman, 1985). However, machine learning approaches, including Random Forest (RF) and artificial neural networks (ANN), have gained traction for their ability to model non-linear relationships and improve predictive accuracy in transport studies (Hagenauer and Helbich, 2017; Ma and Zhang, 2020). These methods, by not relying on strict parametric assumptions, demonstrate greater predictive capacity and better interpretation of variable interactions (Jamal et al., 2021; Ullah et al., 2021; Zahid et al., 2020).

Hagenauer and Helbich, (2017) assessed the predictive effectiveness of seven machine learning classifiers, including support vector machines (SVM), Bagging (BAG), artificial neural networks (ANN), and RF, for travel mode selection based on travel diary data from the Netherlands. RF achieved the highest accuracy (91.4%), followed by Bagging and SVM, highlighting the significance of socio-demographic characteristics, trip purpose, and distance. RF demonstrated its capability to handle complex, non-linear relationships among variables, providing an advantage over the logit model. Ma and Zhang (2020) used an ANN model to predict mode choice behavior, obtaining higher accuracy and robustness compared to traditional models. The increasing use of machine learning algorithms in transportation studies reflects a shift toward more sophisticated methods that better capture the complexity of human behavior.

While the existing literature provides valuable insights, research on carpooling in Bogotá and other cities in the Global South remains limited, particularly regarding informal and dynamic ridesharing models. Expanding research to diverse settings is essential to capturing the diversity of travel behaviors and institutional contexts, as well as the broader implications of carpooling adoption in complex urban environments. Furthermore, methodological limitations in existing research hinder the ability to capture the intricate behavioral patterns that shape participation in ridesharing schemes. Addressing these gaps is essential for developing strategies that enhance the effectiveness and sustainability of carpooling as a viable mobility alternative in rapidly growing cities.

3. Method

This section presents the methodological approach, which focuses on modeling the stated likelihood of carpooling adoption using a binomial dependent variable derived from a stated preferences experiment. The approach is divided into four sections: Sample size and sociodemographic characteristics; survey design; discrete choice modeling framework and machine learning modeling framework. Bogotá (Colombia) was our study area. Fig. 1 exhibits a flowchart of the methodology, highlighting the key features of the methods. The following sections explain the process in detail.

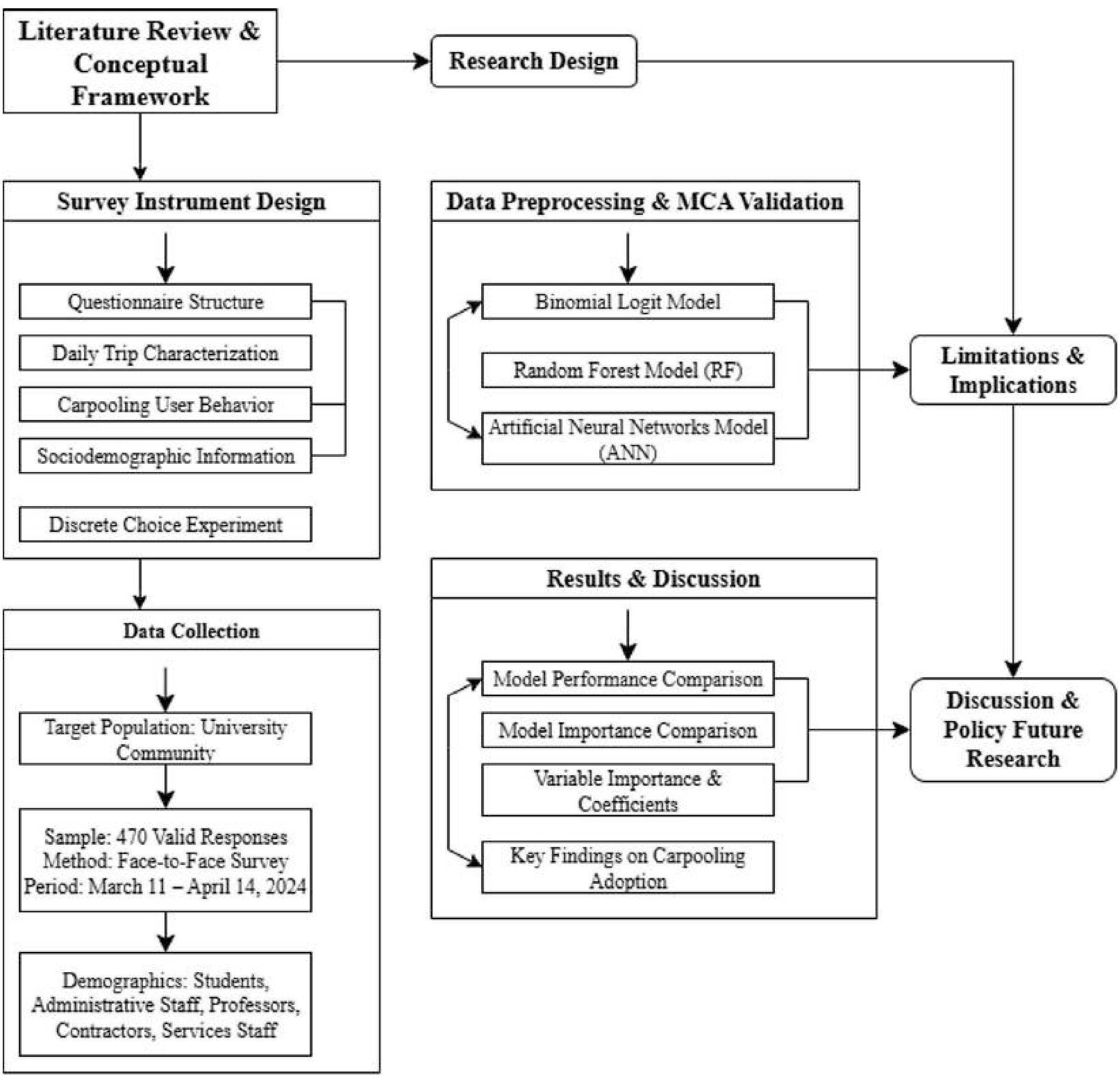

Fig. 1. Flowchart of the methodology.

3.1. Survey design

The survey design covered five key sections to understand potential car-pooling users' mobility patterns and characteristics. (1) The characterization of daily trips aimed to identify current mobility patterns through questions about the frequency, origin, and destination of trips to universities, travel schedules, modes of transport, travel times, and weekly expenses. (2) Section on carpooling use focused on users of this service, obtaining details about their last trip, such as fare, duration, waiting times, and vehicle characteristics, as well as motivation for its use, delays, preferences toward the driver, and the substituted mode of transport. (3) Vehicle ownership was investigated to determine personal vehicle availability, types, number, and availability of parking. (4) Sociodemographic information, collected data on gender, age, educational level, role in the university community, and household income. This approach provided a robust foundation for exploring mobility dynamics and the potential impact of the service. Finally, (5) the Stated Preferences (SP) section presented respondents with a set of hypothetical scenarios to assess their likelihood of using carpooling under different conditions. Respondents evaluated their willingness to use the service on a four-point Likert scale ("I would never use it", "Unlikely", "Likely", "Very likely"). The SP scenarios were generated through an orthogonal experimental design (Myers et al., 2016; Dean et al., 2017). The design resulted in 36 scenarios, divided into four blocks (9 scenarios per block), meaning each respondent replied to 9 different scenarios. In each case, respondents were asked the following question: "*Assuming that an informal carpool service is available for your daily commute to and from university, how likely would you be to use the service under the following* conditions?". Table 1 presents the variables used in the survey, including the dependent variable—stated intention to use carpooling—and the independent attributes considered in the experimental design, their categorization, and the references from the literature that support both the inclusion of said variables and their categorization. The questionnaire also included questions on trip characteristics (frequency, mode, cost, and time), vehicle ownership, sociodemographic information, and motivational factors related to carpooling use. The Appendix presents the definition of variables and their relevance in adopting carpooling, including types of variables, levels, key drivers of carpooling adoption, and references.

Each scenario was graphically displayed to improve comprehension and facilitate comparison, aiming to obtain more consistent and accurate responses (see Fig. 2). To maintain heterogeneity in the results, the 36 scenarios from the orthogonal design were divided into four blocks, and we sought to collect approximately the same number of responses for each block, ensuring balanced representation of the variables of interest. In total, 543 surveys were conducted, of which 470 were valid. Each participant evaluated nine scenarios, taking approximately 15 min to complete the questionnaire.

3.2. Sample size and data collection

The study population consisted of students and faculty members from public and private higher education institutions recognized by the Ministry of National Education of Colombia. The information was sourced from the National Higher Education Information System – SNIES (MinEducación, 2023); this population totaled 385,534 people (344,469 students and 41,065 faculty members).

The sample size was calculated using the method proposed by Johnson and Orme (1996), considering a confidence level of 95% (Z = 1.96), a margin of error of 5% (E = 0.05), and a success rate of p = 0.5. Based on these parameters and the population size (N = 385,534), a minimum sample size of 384 individuals was obtained in Eq. (1).

$$n = \frac{N^{*}Z^{2*}p^{*}(1-p)}{E^{2*}(N-1) + Z^{2*}p^{*}(1-p)} \approx 383.99 \rightarrow n = 384 \quad (1)$$

Data collection was conducted in person between March 11 and April

Table 1
Variables in the stated preference survey.

Variable	Categories/Scale	Type	Definition	References
Dependent: Carpooling use	1 = "Would never use it" 2 = "Unlikely" 3 = "Likely" 4 = "Very likely" Binary recoding: 0 = {Never, Unlikely}, 1 = {Likely, Very likely}	Ordinal (Likert) Binary	Stated intention to use carpooling under experimental scenarios (fare, punctuality, vehicle size, occupants, period).	Survey design
Service fare (COP)	4,500 5,500 6,500	Categorical ordinal	Price of the service in the scenario (value in COP). Assesses cost sensitivity.	(Abrahamse and Keall, 2012; Bulteau et al., 2019; Chaube et al., 2010; Delhomme and Gheorghiu, 2016; Gargiulo et al., 2015; Gheorghiu and Delhomme, 2018; Lee et al., 2016; Neoh et al., 2017; Olsson et al., 2019; Wang et al., 2019a; Shaheen and Cohen, 2019; Wilkowska et al., 2018)
Trip period	6:00–9:00 9:00–17:00 17:00–20:00	Ordinal categorical	Travel time slot (peak/off-peak).	(Abrahamse and Keall, 2012; Bulteau et al., 2019; Chaube et al., 2010; Ciari and Axhausen, 2012; Delhomme and Gheorghiu, 2016; Gheorghiu and Delhomme, 2018; Gurumurthy and Kockelman, 2020; Lee et al., 2016; Monchambert, 2020; Neoh et al., 2017; Olsson et al., 2019; Wang et al., 2019a; Shaheen and Cohen, 2019)
Vehicle size	Small Medium Large	Ordinal categorical	Vehicle capacity/segment (related to number of potential occupants, comfort, and environmental perception).	(Abrahamse and Keall, 2012; Amey et al., 2011; Dorner and Berger, 2016; Gheorghiu and Delhomme, 2018; Lee et al., 2016; Neoh et al., 2017; Wang et al., 2019b)
Occupants / Travel companions	Unknown men Unknown men and women Unknown women Known	Categorical nominal	Composition of travel companions (gender and familiarity). Assesses trust and safety.	(Chaube et al., 2010; Correia et al., 2013; Dorner and Berger, 2016; Delhomme and Gheorghiu, 2016; Gargiulo et al., 2015; Gheorghiu and Delhomme, 2018; Lee et al., 2016; Neoh et al., 2017; Olsson et al., 2019; Monchambert, 2020)
Service punctuality (delay at start)	0–5 min 5–10 min 10–20 min	Categorial ordinal	Expected delay at the start of the trip due to coordination or waiting for occupants.	(Abrahamse and Keall, 2012; Amey et al., 2011; Correia et al., 2013; Delhomme and Gheorghiu, 2016; Dorner and Berger, 2016; Lee et al., 2016; Wilkowska et al., 2018)

Note: References supporting the selection and categorization of variables are provided in the appendices and in the references section.

Fig. 2. Example of a graphically displayed scenario.

14, 2024. A team of 7 people were hired to apply the survey (1 coordinator and 6 pollsters). The team was previously trained through a standardized session covering (i) ethical and confidentiality guidelines, (ii) technical aspects of the LimeSurvey platform, and (iii) standardized procedures for approaching potential respondents within university campuses.

The survey was conducted on-site across 28 universities in Bogotá. To enhance randomness, pollsters approached students and staff at different campuses, on various days of the week, and at different times of the day. Respondents were selected by intercepting individuals in publicly accessible areas within the universities, without applying any predefined selection criteria. While this approach does not yield a fully probabilistic sample, it reduces location and time biases and provides a diverse representation of university students. No financial or material incentives were offered to respondents, and a total of 470 valid responses were obtained. Before the final application, a pilot phase was conducted to validate the survey design. Fig. 3 shows the spatial location of the participating university institutions in the urban area of the city.

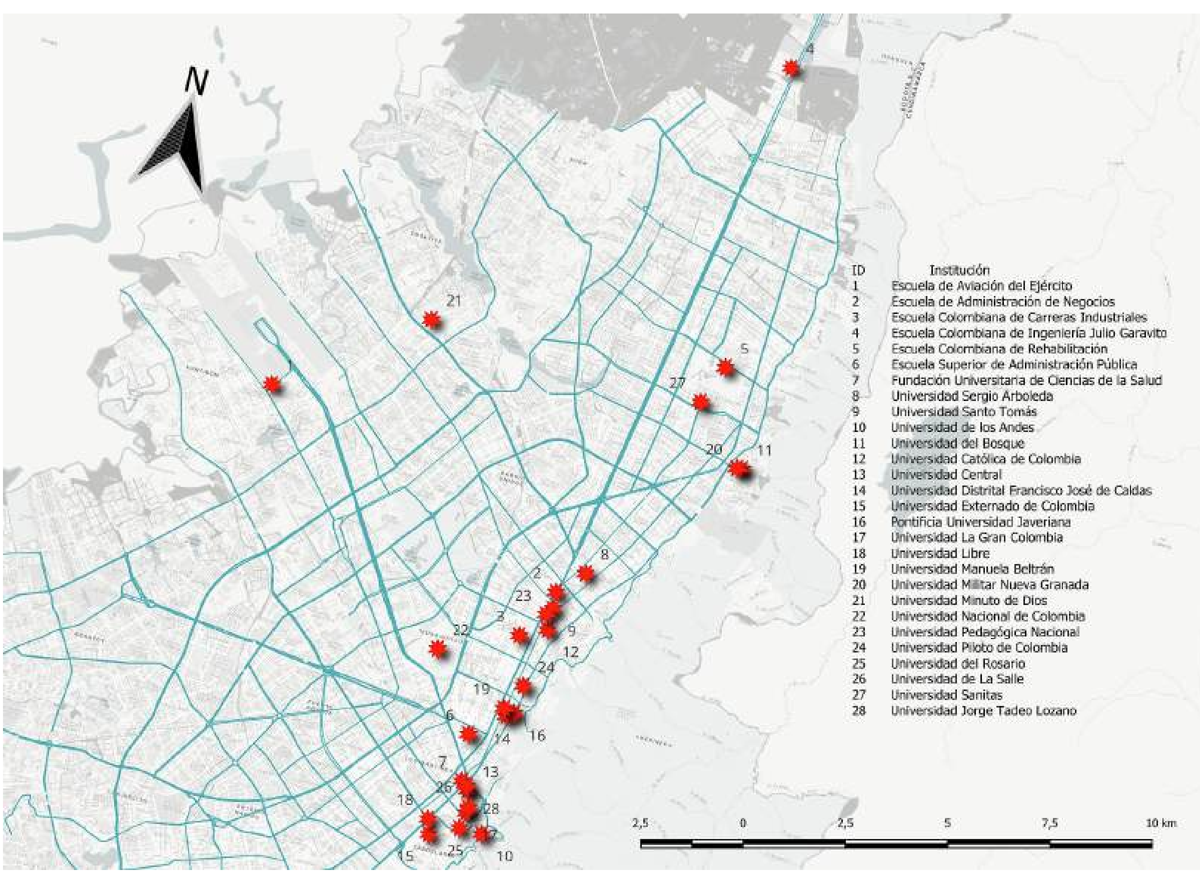

Fig. 3. Spatial distribution of the universities surveyed in the urban area of Bogotá.

3.3. Case study and sociodemographic profile of respondents

The case study focuses on Bogotá (Colombia) and analyzes members of university communities as a representative segment for assessing potential carpooling adoption. This population group was selected due to its high travel frequency, spatial concentration, and potential for implementing shared mobility alternatives within institutional environments. Table 2 provides a comprehensive overview of the sociodemographic composition of the 470 valid respondents, including gender, age, socioeconomic strata, monthly household income, and institutional role. The sample presents adequate diversity across demographic and socioeconomic variables, ensuring the representativeness required for stated preference analysis. Additionally, to evaluate the representativeness of the sample in relation to the university population of Bogotá, the Appendix (see Table A.4) includes a comparative analysis of the principal sociodemographic and academic characteristics of the respondents in conjunction with the official statistics reported by MinEducación (2023) – SNIES.

Regarding previous experience with carpooling, approximately 20% of respondents reported having shared a car at least once, while a smaller proportion indicated having also acted as drivers (13%), and passengers (7%). However, for analytical purposes, this study focuses exclusively on their role as passengers when evaluating willingness to adopt carpooling.

Table 2
Sample characteristics.

Variable	Variable levels	Frequency	% of sample
Gender	Man	240	51.06%
	Women	228	48.51%
	Other	1	0.21%
	I prefer not to answer	1	0.21%
Age	18 to 24 years old	267	56.81%
	25 to 34 years	83	17.66%
	35 to 44 years	45	9.57%
	45 to 54 years	51	10.85%
	55 to 64 years	15	3.19%
	Under 18 years old	7	1.49%
	Over 65 years old	2	0.43%
Socioeconomic strata[a] based on Cantillo-García et al. (2019)	1	8	1.70%
	2	79	16.81%
	3	166	35.32%
	4	121	25.74%
	5	52	11.06%
	6	44	9.36%
Monthly household income (MMS[b]**)**	Between 1 MMS and 3 MMS	143	30.43%
	Between 3 MMS and 6 MMS	141	30.00%
	Less than 1 MMS	15	3.19%
	More than 6 MMS	134	28.51%
	I prefer not to answer	37	7.87%
Role	Undergraduate	290	61.70%
	Postgraduate	21	4.47%
	Full-time Faculty	43	9.15%
	Adjunct Faculty	29	6.17%
	Administrative Staff	55	11.70%
	Contract-based Staff	18	3.83%
	Permanent Staff	12	2.55%
	General Services Staff	3	0.64%
	Other	5	1.06%
Educational level	Baccalaureate	221	47.02%
	Other	2	0.43%
	Postgraduate	92	19.57%
	University professional	69	14.68%
	Technician/ Technologist	86	18.30%

[a] *Official information on socioeconomic stratification for public utility services is available at: https://www.dane.gov.co/index.php/servicios-al-ciudadano/servicios-informacion/estratificacion-socioeconomica.*
[b] *MMS: Monthly Minimum Salary.*

3.4. Discrete modeling framework

For the model and variable selection, a backward stepwise method was applied, iteratively, eliminating those without statistical significance ($p < 0.05$) until an optimal model with the most relevant variables was obtained (De la Fuente, 2020). Initially, we used an ordered logit model and a partial ordered logit model, shown in Eq. (2). Although the ordered logit showed an acceptable early fit, the Brant (1990) test revealed violations of the assumption of parallelism of odds, particularly in variables such as price, vehicle type, gender, and age, which compromised its validity. This model allowed us to analyze all interactions between variables, discarding second-order and higher interactions due to lack of statistical significance ($p > 0.05$) (Burnham and Anderson, 2004; Fox, 2008; Hastie et al., 2009). The partial ordered model, which relaxes the assumption of parallelism, provided a more flexible fit but showed signs of overfitting, such as a high chi-square value and a high number of residual degrees of freedom, indicating an insufficient representation of the underlying relationships in the data. Both models were evaluated using criteria such as AIC, BIC, pseudo-R^2 likelihood tests (Cox and Snell, 1990; McFadden, 1974b; Nagelkerke, 1991), residuals, and the Wald test. Those models were discarded as the data did not meet the theorical assumptions. These results suggest the need to explore alternative approaches, such as binomial logit model, to more accurately capture the complexity and variability of the data.

$$L_k(X) = log\left(\frac{P(Y \leq k|X)}{P(Y > k|X)}\right) = \alpha_k - \beta_1 X_1 - \beta_2 X_2 - \cdots - \beta_p X_p \qquad (2)$$

Where:

- $L_k(X)$: logarithm of the cumulative probabilities of being in the category k or less.
- $P(Y \leq k|X)$: probability that the dependent variable Y is less than or equal to the category k, given the variable X.
- $P(Y > k|X)$: probability that Y is greater than k, given X.
- α_k: threshold associated with the category k.
- $\beta_1, \beta_2, \cdots, \beta_p$: regression coefficients for the predictor variables $X_1, X_2, \cdots, X_p$.

To estimate a binomial logit, we needed to collapse the levels of the dependent variable. To support this decision, we conducted a Multiple Correspondence Analysis (MCA) to identify latent patterns and underlying relationships (Jolliffe, 2002; Lawless, 2002). The biplot in Fig. 4a visually represents the MCA results for the four original categories of the dependent variable ("I would never use it", "Unlikely", "Likely", and "Very Likely"). In this biplot, each point represents a category, and the proximity between points indicates similarity in their patterns of responses. The ellipses drawn around these points represent the confidence regions for each category. As observed in Fig. 4a, the ellipses for the original four categories largely overlap, suggesting that these categories are not clearly distinct or separable in the factor space, making it difficult to differentiate user behavior across these granular levels. This contrasts with Fig. 4b, which illustrates the clear separation achieved after collapsing the dependent variable into two new levels ("No" and "Yes"). Here, the non-overlapping ellipses demonstrate a more distinct clustering, thereby facilitating a robust binomial analysis. This finding reinforced the decision to collapse the dependent variable, facilitating the analysis of the effects between users and the relationships between the independent variables, following theoretical recommendations (Agresti, 2018). Hence, the variable was transformed into a binomial version, grouping the original categories "I would never use it" and "Unlikely" as "No," while "Likely" and "Very Likely" were grouped as "Yes".

After transforming the variables, our study employed a binomial

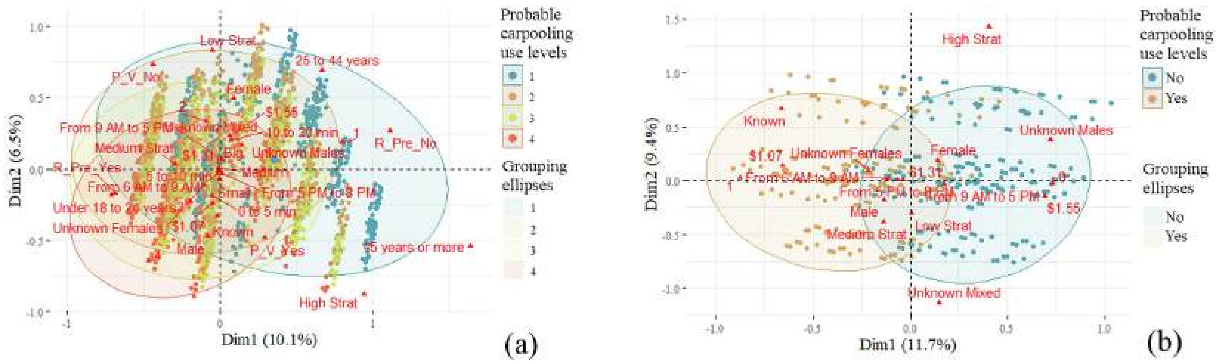

Fig. 4. Multiple Correspondence Analysis biplot showing the distribution of dependent variable categories. (a) Original four-level Likert scale, with overlapping ellipses indicating indistinct categories. (b) Collapsed binomial variable, showing clearly separated cluster.

logit model (see Eq. (3)) to estimate the probability of service use. This probability is defined in terms of systematic utilities that depend on several independent variables, allowing for a detailed analysis of the factors that influence the choice.

$$L(X_i) = log\left(\frac{P(Y_i = 1|X_i)}{P(Y_i = 0|X_i)}\right) = \alpha - \beta_1 X_{i1} - \beta_2 X_{i2} - \cdots - \beta_p X_{ip} \tag{3}$$

Where:

- $P(Y_i = 1|X_i)$: probability that the event of interest (for example, success, presence of a characteristic, etc.) occurs, given a set of explanatory variables X_i.
- $P(Y_i = 0|X_i)$: probability that the event of interest does not occur, given the same set of variables X_i, and is complementary to the previous one.
- α: intercept term or constant of the model.
- β_j: coefficient associated with the independent variable X_{ij}.
- X_{ij}: j-th independent variable associated with the i-th individual or observation.
- p: total number of independent variables in the model.

The independent variables with more than two categories were transformed into unordered factors, eliminating any implicit hierarchy and allowing for modeling without order assumptions (Kutner et al., 2005). Each categorical variable was assigned a specific reference level to facilitate interpretation of the estimated coefficients. For example, reference levels were set to "6 AM to 9 AM" for travel time, "$4,500.00″ for price, "Small" for vehicle size, "Unknown Men" for travel company, "0 to 5 min" for punctuality, "Low strata" for socioeconomic level, and "Under 18 to 24 years" for age range. These references enable evaluation of how other levels of the variables affect the probabilities of the response variable compared to these starting points.

3.5. Machine learning modeling framework

Our study estimated a binomial logit and then used RF and ANN for validation purposes. This approach leverages the complementary strengths of different paradigms: while the logit model offers high interpretability for policy recommendations, machine learning models like RF and ANN serve as a benchmark to assess if complex, non-linear patterns were overlooked. Analyzing these three approaches concurrently allows for a robust comparison, confirming whether the direct effects identified by the logit model sufficiently explain the behavioral patterns or if more intricate dynamics are at play (Hagenauer and Helbich, 2017; Ma and Zhang, 2020). Although the ANN model showed limitations with our specific dataset, its inclusion was vital for a comprehensive evaluation of state-of-the-art methods in this context. The Random Forest model used is a supervised learning algorithm that combines multiple decision trees using the bagging method (sampling with replacement), reducing variance and improving accuracy. Its ability to handle high-dimensional data, integrate categorical and continuous variables, and assess variable importance makes it versatile for classification and regression problems, as well as robust against overfitting (Breiman, 2001; Liaw and Wiener, 2002). The final prediction in a Random Forest is obtained by aggregating individual predictions ($h_t(X)$) from T trees in the ensemble, as shown in Eq. (4):

$$\hat{y} = mode(h_1(X), h_2(X), \cdots, (h_t(X)), \tag{4}$$

Where:

- X: set of input features.
- $h_t(X)$: prediction of the t-th tree.
- $\hat{y}$: final prediction, calculated as the mode (for classification) or the average (for regression) of the individual predictions.

On the other hand, Artificial Neural Networks used (see Eq. (5)), are highly effective in modelling complex non-linear relationships and useful in transport applications, when refining their performance by adjusting hyperparameters or including additional layers (Heaton, 2018; Simon, 2010).

$$\hat{y} = g\left(\sum_{j=1}^{M} \omega_j^{(2)} * f\left(\sum_{i=1}^{N} \omega_{ij}^{(1)} X_i + b_j^{(1)}\right) + b^{(2)}\right) \tag{5}$$

Where:

- $X = (X_1, X_2, \cdots, X_n)$: input characteristics.
- $\omega_{ij}^{(1)}$: weights between the input i neuron j in the hidden layer.
- $b_j^{(1)}$: bias associated with the neuron j in the hidden layer.
- f: activation function of the hidden layer, such as sigmoid or tanh.
- $\omega_j^{(2)}$: weights between the neuron j in the hidden layer and the output.
- $b^{(2)}$: output bias.
- g: output activation function (such as sigmoid for binomial classification or softmax for multiclass classification).
- $\hat{y}$: output prediction.

4. Results

The results of the modeling approaches are presented in Table 3. Outcomes of the binomial logit model show that several variables significantly impact the probability of carpooling adoption. Notably, traveling between 9 AM and 5 PM reduces the probability of use (β = -0.22, p-value < 0.01) compared to the reference period between 6 AM to 9 AM, while the time slot from 5 PM to 8 PM is not significant (β =

Table 3
Modeling results.

Variable	Binomial Logit Model β value	Std. Error	*p*-value	Sig.	RF Model β value	Std. Error	*p*-value	Sig.
Intercept	0.18	0.19	0.33		0.24	0.21	0.24	
Schedule: 5 PM to 8 PM	−0.04	0.08	0.62		−0.02	0.09	0.84	
Schedule: 9 AM to 5 PM	−0.22	0.08	0,00	**	−0.20	0.09	0.03	*
Service fee: $1.31 USD	−0.49	0.08	1.16e-09	***	−0.50	0.09	2.22e-08	***
Service fee: $1.55 USD	−1.06	0.08	< 2e-16	***	−1.05	0.09	< 2e-16	***
Vehicle Type: Large	−0.24	0.08	0.00	**	−0.25	0.09	0.00	**
Vehicle Type: Medium	−0.07	0.08	0.36		−0.11	0.09	0.22	
Travel companions: Acquaintances	1.10	0.09	< 2e-16	***	1.03	0.10	< 2e-16	***
Travel companions: Unknown mixed	0.42	0.09	6.46e-06	***	0.46	0.10	1.10e-05	***
Travel companions: Unknown women	0.73	0.09	1.32e-14	***	0.76	0.11	8.32e-13	***
Delay: 10 to 20 min	−0.87	0.08	< 2e-16	***	−0.80	0.09	< 2e-16	***
Delay: 5 to 10 min	−0.38	0.08	2.75e-06	***	−0.41	0.09	6.71e-06	***
Gender: Male	0.14	0.07	0.04	*	0.13	0.08	0.09	.
Undergraduate student	0.23	0.13	0.08	.	0.14	0.15	0.35	
Socioeconomic strata: High	−0.21	0.11	0.06	.	−0.14	0.12	0.26	
Socioeconomic strata: Middle	0.03	0.09	0.71		0.08	0.10	0.41	
Own vehicle: Yes	0.16	0.07	0.03	*	0.11	0.08	0.16	
Age: 25 to 44 years	−0.02	0.13	0.89		−0.11	0.14	0.43	
Age: 45 years or older	−0.69	0.17	3.26e-05	***	−0.70	0.18	0.00	***
Null deviance	5805.8 on 4211 df				4646.6 on 3370 df			
Residual deviance	5249.5 on 4193 df				4236.7 on 3352 df			
AIC	5287.5				4274.7			

Significance codes: '***' $p \leq 0.001$, '**' $p \leq 0.01$, '*' $p \leq 0.05$, '.' $p \leq 0.1$, ' ' $p \leq 1$.
Dispersion parameter for the binomial family set to 1.
Number of Fisher Scoring iterations: 4.

-0.04, *p*-value = 0.62), suggesting similar characteristics to the reference time. Moreover, the service fee shows a strong negative relationship, with significant decreases in the probability of use at $1.31 USD (β = -0.49, *p*-value < 0.001) and $1.55 USD (β = -1.06, *p*-value < 0.001), demonstrating users' sensitivity to costs. Furthermore, punctuality is another key factor, as delays of 5 to 10 min (β = -0.38, *p*-value < 0.001) and 10 to 20 min (β = -0.87, *p*-value < 0.001) significantly reduce the willingness to use.

On the other hand, carpooling with acquaintances significantly increases the likelihood of use (β = 1.10, *p*-value < 0.001), followed by female strangers (β = 0.73, *p*-value < 0.001) and mixed groups (β = 0.42, *p*-value < 0.001). Regarding gender, men are more likely to adopt the service than women (β = 0.14, *p*-value = 0.043). Additionally, car owners are more inclined to use the service (β = 0.16, *p*-value = 0.031). However, individuals over 45 years old show a lower willingness to use the service (β = -0.69, *p*-value < 0.001), compared to those aged 18 to 24.

In contrast, some variables do not show significant effects or are moderately significant. High-income households show a slight reduction in the probability of use (β = -0.21, *p*-value = 0.06), while the middle socioeconomic strata shows no significant differences compared to the low socioeconomic strata (β = 0.03, *p*-value = 0.71). Undergraduate students have a marginal preference for the service (β = 0.23, *p*-value = 0.077). People aged 25 to 44 do not show a significant effect on carpooling adoption (β = -0.02, *p*-value = 0.89) compared to the reference category (18 to 24 years). These findings underline the influence of sociodemographic factors on adoption decisions, although not all variables have the same degree of statistical relevance. Finally, regarding the type of vehicle, large vehicles are associated with a significant decrease in the probability of accepting the service (−0.24, *p*-value < 0.01), suggesting that respondents prefer smaller vehicles for carpooling. In contrast, medium-sized vehicles have no significant effect (−0.07, *p*-value = 0.36), implying that their size does not influence preference for the service compared to small vehicles. Moreover, fit metrics such as residual deviance and AIC reflect the overall performance of the model. The results of the RF model show that the coefficient values are quite similar to those of the binomial logit model, while the signs of the coefficients are identical. This similarity provides consistent support for the key factors identified by the logit model. A notable observation is the difference in the statistical significance for male gender, where the Logit model identifies a significant effect, while the RF model does not (*p*-value = 0.04 and *p*-value = 0.09 respectively). This outcome is consistent with the distinct analytical objectives of each approach: the Logit model, with its emphasis on statistical significance, serves as the basis for our direct policy recommendations, whereas the RF model confirms the overall variable importance in a broader, non-linear context. While the ANN model was also employed to investigate non-linear relationships, it demonstrated lower performance (Accuracy: 0.63, Kappa: 0.25) likely due to the size of our training data. This finding, while a negative result, is a key insight for future research, as it highlights the importance of selecting appropriate models and metrics for imbalanced datasets.

The confusion matrix in Table 4 verified the predictive performance of the models. The logit model utilized all obtained responses, whereas the RF and ANN models employed 80% of the responses for training and reserved the remaining 20% for model testing. The binomial logit and RF models performed similarly, while the ANN performed worse. Consequently, the ANN results were discarded due to the limited number of observations for model training. The accuracy and its confidence interval (CI) showed better performance for the binomial logit, with the CI being statistically significant for all models. Moreover, sensitivity and

Table 4
Confusion matrix and model performance.

	Binomial Logit		RF		ANN	
	Prediction					
Reference	No	Yes	No	Yes	No	Yes
No	1757	881	350	179	331	175
Yes	536	1038	108	204	127	208
Accuracy	0.66		0.65		0.63	
95% CI	(0.65, 0.68)		(0.62, 0.68)		(0.56, 0.66)	
p-value	2.2e-16		1.918e-10		4.397e-07	
Sensitivity	0.77		0.75		0.68	
Specificity	0.54		0.53		0.57	
Kappa	0.31		0.29		0.25	

specificity align with the confusion matrix results. Although Kappa values indicate fair agreement between model predictions and true classes, it should be avoided as a performance measure in classification in unbalanced cases (Delgado and Tibau, 2019).

5. Discussion

Informal carpooling in Bogotá offers notable benefits, particularly in terms of flexibility and community-driven innovation. The absence of standardized fare structures creates room for price negotiation, allowing supply and demand dynamics shape the willingness to pay, an aspect that can be attractive to users. However, during peak hour surges or in special events, this flexibility can also result in steep fare increases and disputes between drivers and passengers, as there is no formal mechanism to prevent excessive pricing. Ad hoc solutions—such as transparent, community-based ride agreements or cooperatives—can help passengers perceive fair value. Transitioning to a formalized, regulated system could potentially enable authorities to introduce targeted subsidies, tiered fares, or dynamic pricing tools, improving accessibility, particularly for low-income users who rely on informal transport. Expanding partnerships with employers and educational institutions could also enhance formal cost-sharing structures while preserving the adaptability that has made informal carpooling popular.

An analysis of the model results highlights key factors influencing carpooling adoption, including vehicle ownership, travel schedules, vehicle type, rideshare companions, gender, age, and price sensitivity. In high-motorization countries like the US and France, car ownership correlates with a lower tendency to rideshare, as users prioritize independence and convenience (Delhomme and Gheorghiu, 2016; Neoh et al., 2017). In Bogotá, where motorization rates are lower, carpooling emerges as an attractive alternative for those without personal vehicles or those seeking to reduce mobility costs. Price sensitivity plays a crucial role, as rising service costs reduce willingness to participate, a trend also observed in the US and UK (Gurumurthy and Kockelman, 2020; Neoh et al., 2017). Additionally, long wait times negatively affect perceptions of reliability and efficiency, mirroring findings in Germany and Switzerland (Ciari and Axhausen, 2012; Dorner and Berger, 2016).

"Wheels" effectively addresses these adoption barriers by operating in closed communities where trust is fundamental. By leveraging WhatsApp for real-time coordination, the platform overcomes technological barriers, encouraging adoption through a dynamic and accessible system. This model has proven successful in university settings, where familiarity among users fosters ridesharing. For example, the Universidad de Los Andes, which promoted shared rides in 2010, and Pontificia Universidad Javeriana, which had over 12,000 verified users by 2014, demonstrate how "Wheels" strengthens both mobility and the social fabric among students (Simancas et al., 2024).

Socioeconomic factors and vehicle ownership significantly influence mobility decisions. Higher-income households tend to favor private transport, while middle-income households exhibit more diverse behaviors based on accessibility and cost-benefit perceptions (Bulteau et al., 2019; Gargiulo et al., 2015; Olsson et al., 2019). Our findings indicate that private vehicle ownership plays a key role in carpooling decisions. The lower motorization rate in Bogotá, especially among university communities, may shape the service's adoption patterns, warranting further research.

Notably, individuals who own cars ($\beta = 0.16$) are positively associated with the use of carpooling, as they may perceive it as a flexible and pragmatic strategy for enhancing the efficiency of private transportation while simultaneously reducing costs. This may be related with Bogotá's private vehicle restriction policy, known as *Pico y Placa* (peak and plate), which exempts vehicles carrying three or more individuals, including the driver, as it may encourage shared transportation. According to the Secretaría Distrital de Movilidad (2022), *Pico y Placa* measure reduced vehicle circulation by 10%–15% during peak hours, improving travel times and lowering emissions. Complementary initiatives like *Pico y Placa Solidario*, a voluntary permit allowing vehicle use during restrictions—aim to encourage more rational car use. However, these measures impact different socioeconomic groups unevenly, underscoring the need for inclusive alternatives such as carpooling, which offers both economic and environmental benefits (Buliung et al., 2009; Neoh et al., 2017; Wang, 2011). Data from the Bogotá Mobility Observatory (Secretaría Distrital de Movilidad, 2022), indicate that 28% of carpooling participants do so to reduce costs, while 20% do so to navigate *Pico y Placa* restrictions. Our findings suggest that "Wheels" serves as an alternative to avoid these restrictions, providing valuable insights for shared-vehicle policies.

Sociodemographic factors further shape carpooling demand. Younger users and car owners show greater willingness to share rides, suggesting that informal services could benefit from grassroots awareness campaigns on campuses and in workplaces. Older adults, who are less likely to adopt carpooling, may benefit from simplified tech interfaces or phone-based booking systems. Under a formalized system, policymakers could support outreach initiatives emphasizing cost savings, environmental benefits, and safety measures. Incentives such as financial benefits for compact or electric vehicles, HOV lane privileges, and standardized quality controls could further institutionalize carpooling. The challenge for regulators is to balance the adaptability and local grounding of informal services with the consistency and protection of regulated systems, ensuring that all demographic segments can benefit from a more reliable and inclusive carpooling environment.

Mobility patterns closely align with peak traffic hours, characterized by the highest levels of congestion occurring between 6:00–9:00 a.m. and 5:00–8:00 p.m. Notwithstanding this trend, user preferences for carpooling remain stable during these periods. In contrast, demand drops between 9:00 a.m. and 5:00 p.m., likely reflecting the influence of work and academic schedules. Consistent with our findings, research conducted by the Inter-American Development Bank and the District Mobility Secretariat (BID & SDM, 2022) indicates significant fluctuations in transportation supply and demand throughout the day, underscoring the need for congestion-responsive strategies.

A key challenge in this context is service reliability. In informal carpooling, participants typically manage delays through real-time communication, community ratings, or designated local pick-up zones. While these grassroots strategies establish shared norms around punctuality, they lack enforceable standards to address recurring service inconsistencies. Formalization could help bridge this gap by introducing benchmarks for on-time performance, official pick-up/drop-off locations, and infrastructure improvements that minimize travel uncertainties. Additionally, integrating digital tools for real-time scheduling would enhance reliability by providing accurate, up-to-date information, ultimately increasing trust in the service. However, any formalization efforts must preserve the adaptability and user-driven responsiveness that make informal carpooling an attractive option.

Regarding vehicle size, users prefer smaller cars over larger ones, aligning with prior research (Abrahamse and Keall, 2012; Amey et al., 2011; Dorner and Berger, 2016; Neoh et al., 2017; Wang et al., 2019a). This may be due to cost perceptions, as larger vehicles are often associated with higher fares. While this perception was not directly controlled in our survey, it suggests that users prioritize affordability and efficiency. Small vehicles offer lower maintenance costs, better fuel efficiency, and greater maneuverability in Bogotá's dense traffic. The increasing number of small and medium-sized vehicles in the city—from 991,972 in 2019 to 1,600,231 in 2022 (Secretaría Distrital de Movilidad, 2022)—reinforces this trend.

Trust and familiarity are critical to carpooling participation, particularly when sharing rides with acquaintances. Prior research suggests that lower risk perception and opportunities for social interaction encourage participation (Greene and Hensher, 2010). While users prefer known travel companions, there is also a strong preference for female carpool partners, likely due to perceived safety. Gender differences further influence adoption rates, with men more likely to use carpooling services, consistent with studies showing that men are generally less sensitive to security concerns (Monchambert, 2020; Orozco-Fontalvo et al., 2019). Safety concerns in informal university carpooling present challenges to sustainability. While platforms like "Wheels" have fostered carpooling in closed communities, the lack of regulation raises concerns about road safety, user validation, and fare standardization. The absence of membership verification increases security risks, particularly for women, who are less likely to use unregulated services due to safety concerns (Monchambert, 2020). In Bogotá, where urban insecurity is a persistent issue, enhancing reliability and safety measures could improve carpooling adoption rates among women. Additionally, variable fare contributions can lead to conflicts and perceptions of unfairness (Neoh et al., 2017; Olsson et al., 2019). These factors highlight the need for formalization strategies that ensure security while preserving accessibility. Implementing identity verification, regulating fees, and establishing safety protocols could increase trust and promote broader adoption. However, regulation must strike a balance between control and flexibility to avoid discouraging participation (Wilkowska et al., 2018).

We acknowledge several limitations. First, this study was limited to university communities, as the "Wheels" service was not operating outside them. Second, the majority of those surveyed were undergraduate students, which limited the analysis and may have biased the sample. Third, a key limitation of this study is the exclusion of variables related to the broader transport ecosystem, such as the availability and cost of parking at the university and the quality of public transport access. These factors are known to significantly influence mode choice, and their inclusion would likely provide a more comprehensive understanding of carpooling adoption. Finally, we did not consider the effect of the license restriction measure *Pico y Placa* in the scenarios, which could have provided better insights into its effect on mode choice. Future research could address these limitations by incorporating these additional variables to more accurately model the competitive landscape of mobility alternatives.

6. Conclusions

This study evaluated the factors influencing the use of an informal carpooling service within university communities in Bogotá, conducting a stated preferences survey and estimating both logit and machine learning models. We concluded that the service is popular among students and that factors such as reliability (punctuality), vehicle type, travel companions, and time of day influenced the probability of choosing the service.

This study introduces a methodological approach to address ordinal data violations of the parallelism assumption through Multiple Correspondence Analysis (MCA) in the context of carpooling choice modeling. Our comparative analysis of the logit model and machine learning methods in carpooling choice validates the rationale for employing complementary approaches in transport behavior studies. The binomial logit model provides interpretability for policy implications, a finding reinforced by the consistent variable importance results from the RF model. In contrast, RF offers a balance between predictive accuracy and interpretability, whereas ANN, despite its strength in highly non-linear settings, demonstrates lower performance due to insufficient training data. This comprehensive evaluation, including the performance of ANN, highlights the importance of selecting appropriate metrics for imbalanced datasets and caution against overreliance on the Kappa coefficient. To provide a better understanding of the results, we recommend conducting hybrid approaches, estimating both logit and machine learning models to improve pattern recognition and enhance interpretability.

One of the main results is that trust in fellow travelers and security are determining factors in the use of carpooling. The tendency to share vehicles with acquaintances and, to a lesser extent, with women highlights the importance of creating a safe and trustworthy environment, which can be a significant barrier to the widespread adoption of these services in cities with a high crime index. Therefore, enhancing carpooling security through measures such as driver verification, developing trustworthy platforms, and implementing security protocols could increase women's willingness to use these services.

The comprehensive approach of this research allowed us to identify economic, technological, commercial, regulatory, and behavioral barriers and motivators that influence the success of carpooling services within the studied context. Improving users' connectivity with digital platforms and offering the service features sought by prospective users, as examined in this article, could yield substantial positive outcomes and promote the adoption of carpooling.

Furthermore, implementing carpooling policies requires considering context-specific attributes, including cultural aspects, crime rates, regulation towards shared mobility, motorization rates and the availability and quality of other transport options. In addition, studies should analyze the costs and implications of regulating and formalizing informal carpooling services, since existing evidence suggests this may reduce demand if pricing flexibility is constrained. Future research should assess not only the wider economic benefits but also the social outcomes, including impacts on equity, accessibility, and community acceptance, to determine whether carpooling should be widely adopted or if these informal (popular) initiatives should remain at a low scale. Finally, replicating this study in other urban contexts and at the city level would help capture local variables, such as cultural attitudes toward sharing, safety perceptions, enforcement of peak-and-plate schemes, and integration with public transport—that shape carpooling's potential and guide tailored policy interventions.

CRediT authorship contribution statement

César A. Merchán-Núñeza: Writing – original draft, Investigation, Formal analysis, Data curation. **Mauricio Orozco-Fontalvo:** Conceptualization, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Luisa F. Morales-Moreno:** Writing – original draft, Investigation, Formal analysis, Data curation. **Aquiles Darghan:** Writing – review & editing, Methodology, Conceptualization, Investigation, Validation, Visualization. **Sonia C. Mangones M.:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Investigation, Conceptualization. **Lenin A. Bulla-Cruz:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Methodology.

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.

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Appendix

Table A.1
Definition of variables and their relevance in adopting carpooling.

Variable	Definition and relevance
Carpooling service fee	The carpooling service fee is the amount participants pay to share a vehicle, influenced by trip distance, number of participants, and associated costs: fuel, tolls, parking (Shaheen et al., 2016). While carpooling may be free in some cases, organized platforms often include administrative or service fees. Furthermore, fees reflect the cost-benefit perception within university communities, a key factor in adopting the service (Abrahamse and Keall, 2012; Neoh et al., 2017). Additionally, digital platforms have improved the management of dynamic fares, enhanced efficiency and promoted carpooling use (Gheorghiu and Delhomme, 2018; Shaheen and Cohen, 2019).
Trip period	Travel time slots in cities like Bogotá are crucial for urban planning and mobility policies, influencing traffic congestion, air quality, and public transport efficiency (BID & SDM, 2022). Key time slots in Bogotá include the morning rush hour (6:00 am – 9:00 am), which generates high traffic and stress for travelers (Bulteau et al., 2019; Gheorghiu and Delhomme, 2018). Intermediate hours (9:00 am – 5:00 pm) see decreased congestion, though moderate levels persist depending on specific activities (Ciari and Axhausen, 2012; Olsson et al., 2019). The evening rush hour (5:00 pm – 8:00 pm) also features high congestion, with intense flows to homes (Neoh et al., 2017; Wang et al., 2019a), while traffic decreases at night and early morning (8:00 pm onwards), although special events may temporarily increase congestion (Gurumurthy and Kockelman, 2020; Monchambert, 2020). Strategies to optimize mobility include incentives for off-peak travel, teleworking, and infrastructure improvements, which have proven effective in other cities (Gheorghiu and Delhomme, 2018; Shaheen and Cohen, 2019), contributing to reduced congestion and greenhouse gas emissions (Abrahamse and Keall, 2012; Lee et al., 2016).
Vehicle size	Vehicle size is a fundamental variable in carpooling, affecting passenger capacity, efficiency, and sustainability (Gheorghiu and Delhomme, 2018; Wang et al., 2019a). A larger vehicle can carry more people, improving efficiency and reducing the number of vehicles in circulation, but the choice depends on drivers' availability and preferences (Lee and Savelsbergh, 2015; Lee et al., 2016). Larger vehicles are also more resource-efficient, reducing fuel consumption per passenger and contributing to decreased congestion and emissions (Neoh et al., 2017). However, some users may prefer smaller vehicles for greater comfort and privacy (Dorner and Berger, 2016). Promoting high-capacity vehicles can effectively reduce costs and environmental impact (Abrahamse and Keall, 2012; Amey et al., 2011).
Occupants / Travel companions	Carpooling occupants are categorized based on their relationship with the driver and other passengers, impacting on the travel experience and willingness to participate (Chaube et al., 2010; Lee et al., 2016). Unknown men may raise safety concerns, although digital platforms foster trust through rating systems. The mixing of unknown men and women is common, but some may feel uncomfortable depending on social norms (Dorner and Berger, 2016). The exclusive presence of unknown women may increase participation willingness due to a perception of greater safety (Correia et al., 2013; Gargiulo et al., 2015; Olsson et al., 2019). Traveling with acquaintances, such as friends or family, is preferred due to increased trust and convenience, alleviating safety and interaction concerns (Correia et al., 2013; Gheorghiu and Delhomme, 2018). Trust is a key factor in carpooling adoption, and platforms providing rating and verification mechanisms help mitigate concerns (Delhomme and Gheorghiu, 2016; Neoh et al., 2017).
Punctuality (delay when starting the trip)	Punctuality is crucial for carpooling acceptance, with delays arising from occupant coordination or traffic (Abrahamse and Keall, 2012; Lee et al., 2016). Delays of up to five minutes are generally acceptable, but those of five to ten minutes can cause discomfort, especially if recurrent (Amey et al., 2011). Delays over ten minutes can significantly affect the passenger experience, leading to distrust in the service and consideration of other transport options (Correia et al., 2013; Dorner & Berger, 2016). Poor punctuality can discourage carpooling if coordination and communication among participants are not improved (Delhomme & Gheorghiu, 2016; Wilkowska et al., 2018). Incentives for schedule compliance can help reduce delays and increase confidence in the system.

Table A.2
Types of variables, levels and references (adapted from Mitropoulos et al. (2021)).

Author(s) year	Location	Categorical Ordinal				Categorical Nominal
		Carpooling service fee ($ USD)	Trip period	Vehicle size	Punctuality of service – delay when starting the trip (min)	Occupants / Travel companions
		1.07	6 AM to 9 AM	Small	0 to 5	Unknown Men
		1.31	9 AM to 5 PM	Medium	5 to 10	Unknown Mixed
		1.55	5 PM to 8 PM	Big	10 to 20	Unknown Women
						Known
Abrahamse and Keall (2012)	New Zealand	●	●	●	●	
Amey et al. (2011)	USA			●	●	
Bulteau et al. (2019)	France	●	●			
Chaube et al. (2010)	USA	●	●			●
Ciari and Axhausen (2012)	Switzerland		●			
Correia et al. (2013)	Portugal				●	●
Deakin et al. (2010)	USA					
Delhomme and Gheorghiu (2016)	France	●	●		●	●
Dorner and Berger (2016)	Germany			●	●	●
Gargiulo et al. (2015)	Italy	●				●
Gheorghiu and Delhomme (2018)	France	●	●	●		●
Gurumurthy and Kockelman (2020)	USA		●			
Lee et al. (2016)	USA	●	●	●	●	●
Monchambert (2020)	France		●			●

(*continued on next page*)

Table A.2 (*continued*)

Author(s) year	Location	Categorical Ordinal				Categorical Nominal
		Carpooling service fee ($ USD)	Trip period	Vehicle size	Punctuality of service – delay when starting the trip (min)	Occupants / Travel companions
		1.07	6 AM to 9 AM	Small	0 to 5	Unknown Men
		1.31	9 AM to 5 PM	Medium	5 to 10	Unknown Mixed
		1.55	5 PM to 8 PM	Big	10 to 20	Unknown Women
						Known
Neoh et al. (2017)	UK	●	●	●		●
Olsson et al. (2019)	Global	●	●			●
Shaheen and Cohen (2019)	USA	●	●			
Wang et al. (2019a)	China	●	●	●		
Wang et al. (2019b)	China					
Wilkowska et al. (2018)	Germany	●			●	

Table A.3
Key drivers of carpooling adoption (adapted from Mitropoulos et al. (2021)).

Author(s) year	Location	Service Factors												
		Sociodemographic					Origin		Service Provider					
		Trip purpose	Income	Gender	Educational level	Age	Travel distance/ time	Lack of PT / frequency	Travel cost	Security / trust	Incentives *	Matching information / Availability	Lack of flexibility	Socialize
Abrahamse and Keall (2012)	New Zealand						●	●	●			●	●	●
Amey et al. (2011)	USA		●				●	●						
Bulteau et al. (2019)	France		●				●		●					
Chaube et al. (2010)	USA						●		●	●	●	●		
Ciari and Axhausen (2012)	Switzerland	●	●				●							
Correia et al. (2013)	Portugal	●	●		●	●				●	●		●	
Deakin et al. (2010)	USA										●	●		
Delhomme and Gheorghiu (2016)	France	●		●			●		●				●	
Dorner and Berger (2016)	Germany							●		●			●	
Gargiulo et al. (2015)	Italy								●	●		●		●
Gheorghiu and Delhomme (2018)	France					●	●	●	●	●				
Gurumurthy and Kockelman (2020)	USA		●		●	●	●							
Lee et al. (2016)	USA	●		●	●	●	●	●	●	●			●	
Monchambert (2020)	France	●	●	●		●	●							
Neoh et al. (2017)	UK		●	●	●	●	●	●	●	●	●	●		
Olsson et al. (2019)	Global			●			●		●	●	●			●
Shaheen and Cohen (2019)	USA	●	●				●		●		●			
Wang et al. (2019a)	China		●				●							
Wang et al. (2019b)	China	●	●			●	●	●	●	●				
Wilkowska et al. (2018)	Germany			●		●			●		●			

*Incentives: Free parking, use of High Occupancy Vehicle (HOV) lanes, ride-sharing services available at a company or university.

Table A.4
Distribution of students and faculty in Bogotá's higher education institutions: A comparative analysis of sample data and official statistics.

Variable	Sample (n = 470)	University population Bogotá*
University role	Students: 85%	Students: 344,469 (89%)
	Professors: 15%	Professors: 41,065 (11%)
Type of institution	Public: 60%	Public: ~55%
	Private: 40%	Private: ~45%
Gender	Women: 48.51%	Women: 51%
	Men: 51.06%	Men: 49%
Average age (years)	Students: 21.5	Students: 20–24
	Professors: 45.3	Professors: No official data available

*Source: National Higher Education Information System – SNIES (MinEducación, 2023). Note: The age of professors is not documented in official university records and could not be included in this table. Therefore, the analyses were conducted solely with the variables reported by the institutions.

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