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Shared mobility during public transport disruptions: Users' perspectives in a Brazilian city☆

Luiza Gagno Azolin[a,b,*], Anna Beatriz Grigolon[a], Antônio Nélson Rodrigues da Silva[b], Karst T. Geurs[a]

[a] University of Twente, Faculty of Engineering Technology, Department of Civil Engineering and Management, the Netherlands
[b] University of São Paulo, São Carlos School of Engineering, Department of Transportation Engineering, Brazil

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ABSTRACT

This study investigates the potential use of shared mobility systems during public transport disruptions. Unlike most studies in the field, our approach focused on users' perspectives, based on a joint revealed preference/stated choice survey with over 1,000 respondents in Rio de Janeiro, Brazil. Spatial analysis and logistic regression reveal that proximity to bike sharing stations, young age and private vehicle ownership increase the chances of shared bikes use. Mixed logit model estimates with stated choice data show cost sensitivity variations among users when choosing between ridesourcing and public transport during disruptions, with proximity to public transport infrastructure favoring ridesourcing as a possible complementary mode. The results highlight the potential of ridesourcing during disruptions, with a high willingness to pay for time savings. In contrast, bike sharing is not considered viable for commuting during public transport disruptions due to unfamiliarity with this service and concerns about traffic and safety.

1. Introduction

Over the past decade, research on transport vulnerability and resilience has grown rapidly, making its application one of the main purposes of international policies and academic discussions associated with crisis management and sustainable urban development (Coaffee et al., 2018). Most studies have focused on operational aspects, examining how transport systems respond to events such as network interruptions, economic or energy crises, and public calamity situations. These studies typically assess the impacts of disruptive events in the availability of transportation modes and how demand can be met by other modes (Azolin et al., 2020; Chan and Schofer, 2016; Morelli and Cunha, 2021; Tian et al., 2024; Wang et al., 2024).

However, little attention has been given to the user perspectives, considering aspects such as their needs, capabilities, and preferences in the face of disruptive circumstances (Chan, 2025; Li and Wang, 2020; Schaefer et al., 2021; Wang et al., 2024). In particular, few studies have been conducted in the Global South, where the availability of alternative travel options is limited, especially for low-income groups. In Brazil, Oestreich et al. (2023) identified greater receptivity toward adopting active mobility in response to the pandemic, while Cardoso et al. (2023) assessed resilience from a gender perspective, including users' perceptions of exposure to

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* Corresponding author at: Department of Civil Engineering and Management, University of Twente. Drienerlolaan 5, 7522 NB, Enschede, the Netherlands.

E-mail address: l.azolin-tessarolo@utwente.nl (L.G. Azolin).

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violence when using public transport. In both studies, questionnaires were designed and applied to gather users' preferences and perspectives.

Shared mobility services, such as shared bike, car, scooter, and ridesourcing, are proliferating worldwide, leading to discussion about their impact on users and public transport. They have the potential to reduce the negative impacts of cars on urban areas, support more inclusive and affordable transport options, and improve user accessibility by increasing choice options and facilitating connections across multiple modes of transport (Lo et al., 2020; Montes et al., 2023; Si et al., 2019). Shared mobility can strengthen transport system resilience by providing reliable alternatives during public transport disruptions, helping maintain daily activities and supporting overall system stability.

Despite the potential benefits of shared mobility services as backup modes during public transport disruptions, very few studies have been conducted to examine the characteristics of users who are able or willing to switch to shared mobility. Existing literature on shared mobility shows that its users tend to belong to specific demographic groups, typically male, young, white, and with education and income levels above population averages (Acheampong et al., 2020; De Chardon, 2019; Duran et al., 2018).

Li and Wang (2020) studied responses to subway failures in China and found that bike sharing is effective for short trips, while ride-hailing services provide direct routes to destinations. Wang et al. (2024) analyzed trip data from Chicago and found that ridesourcing offers adaptive capacity during rail disruptions, but its benefits are not equitably distributed. Chan (2025) used the multi-level perspective to study Hong Kong's dockless bike sharing system during social movements and the pandemic, revealing how resilience arises from interactions between individuals, communities, and institutions. His findings indicate that while structured practices can promote stability, they may also cause social exclusion, highlighting the need for balanced and inclusive policies.

These patterns raise questions about how effectively local systems can meet users' needs and whether people are both willing and able to shift to these modes. Particularly in Brazilian cities, despite infrastructure improvements and the growing use of shared mobility, challenges remain due to social inequalities and limited availability. In Rio de Janeiro, where transportation costs are among the highest in Brazil, shared modes are often used by younger people with higher levels of education and income (Warwar and Pereira, 2022). As the measures adopted are still ineffective in expanding the use of these services, the adequacy of shared mobility infrastructure, as well as the unawareness of users' needs and capabilities, are still issues that deserve further investigation.

As disruptions may trigger behavioral changes (users may consider other modes they otherwise would not have considered), it is relevant to explore how shared mobility can help users make their trips during disruptions, enhancing equitable access and system resilience. This involves not only the availability of transport systems but also considers that some users may experience ignorance or the inability to use other alternatives, reducing their accessibility potential (Tiznado-Aitken et al., 2020). Specially in Brazilian context, where dependence on public transit is high, and access to transport and opportunities is unevenly distributed (Barboza et al., 2021), there is a need to assess the actual potential of shared mobility to support system continuity.

1.1. Research framework

Based on insights from the literature, Fig. 1 presents the research framework. Disruptive events can affect the operation of public transport services and reduce or modify the available transport modes. Contextual factors such as infrastructure access, mode-specific attributes (e.g., travel time, cost), and user-related aspects (e.g., knowledge, willingness, and ability to use certain modes) influence the modal choice process. This choice, in turn, shapes the system response and its resilient capacity. Depending on the outcome, trips may

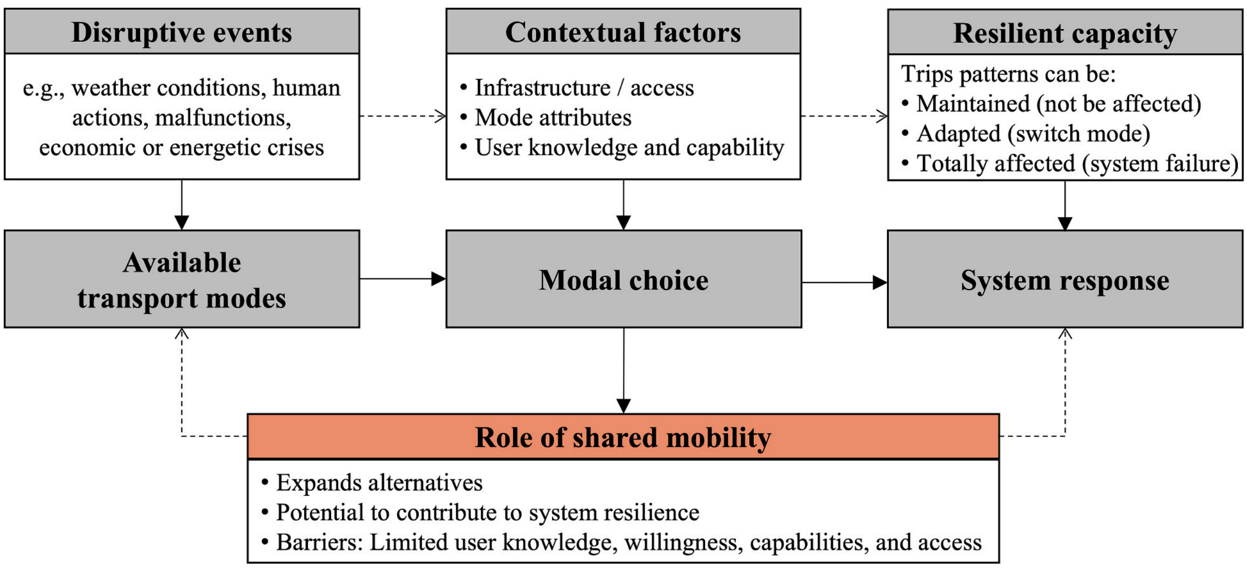

Fig. 1. Research framework diagram.

be maintained (i.e., not affected), adapted (e.g., mode switch), or totally affected (e.g., trip not taken, indicating a system failure from the user perspective). Within this dynamic, shared mobility (e.g., ridesourcing and bike sharing) can expand the set of transport options and enhance resilience. However, this potential is moderated by significant barriers, such as users' limited familiarity with these modes, unequal access, and capabilities.

This research aims to evaluate the potential use of shared mobility services during public transport disruptions. To achieve this, we analyze both public transport users' characteristics and built environment attributes to identify the factors influencing the choice of shared modes (bike sharing and ridesourcing) as alternatives during public transport service interruptions. Additionally, we assess which users already utilize shared mobility, under which circumstances they choose these modes, and evaluate their opinions about these services. We address the following research questions: What are public transport users' perceptions of shared mobility services (bike sharing and ridesourcing)? Are public transport users in Rio de Janeiro willing and able to adopt shared mobility services during public transport disruptions? What user and trip characteristics and mode attributes influence the choice of shared mobility as an alternative to public transport during service disruptions?

Contrasting with the existing literature that predominantly focuses on the supply side, this research contributes to the field by offering a novel perspective centered on the user, considering individual characteristics and preferences, with a particular focus on a Brazilian city context. The transport system supply perspective, the operational effects of disruptions, and how they propagate in the network are outside the scope of this research. Instead, the study considers a scenario in which the respondent's usual mode of transport becomes unavailable, while the rest of the network remains operational. This can be understood as a partial disruption at the mode level, regardless of the specific cause (e.g., network blockage, vehicle breakdown, or other factors preventing the operation of that mode).

This paper is organized into four sections. This introduction provides a brief literature review and identifies the research gap addressed by this study. In Section 2, the materials and methods are described, including the study area, data collection, and analytical approaches. Section 3 presents and discusses the results. Finally, Section 4 offers conclusions and final considerations.

2. Material and methods

This section describes the materials and methods employed in this study to evaluate the potential use of shared mobility services during public transport disruptions in Rio de Janeiro, Brazil. First, we present the study area, highlighting key characteristics of the transport system. Next, we provide details of the data collection process, including the design and application of the joint revealed

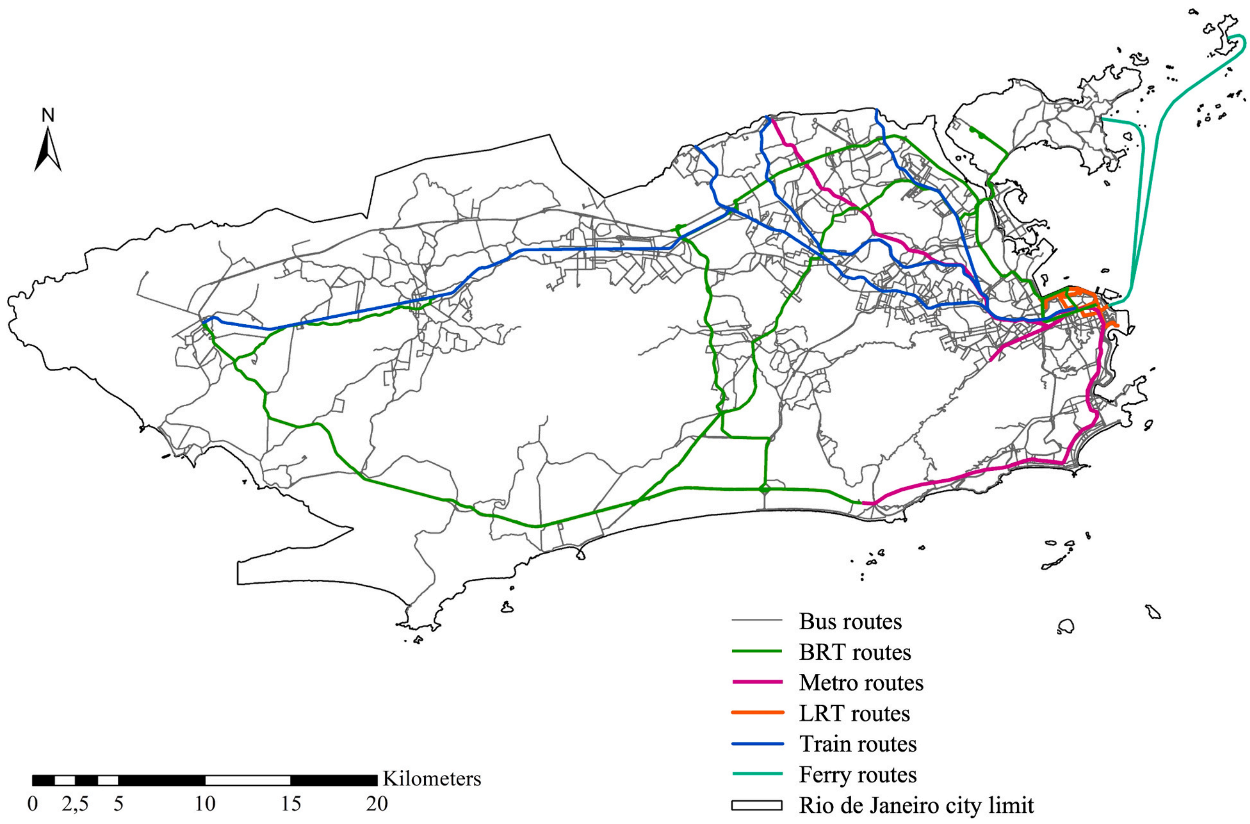

Fig. 2. Public transport routes. Note: BRT – Bus Rapid Transit. LTR – Light Rail Transit.

preference/stated choice survey and the acquisition of built environment data. Finally, we explain the methods used for data analysis.

2.1. Study area

This study was conducted in Rio de Janeiro, a Brazilian city with a population of approximately 6.2 million residents (IBGE, 2023). Rio de Janeiro is located on the coast of the southeastern region of the country, and its transportation system includes conventional buses, Bus Rapid Transit (BRT), metro, trains, Light Rail Transit (LRT), ferries, taxis and vans (Fig. 2). Taxis and vans are outside the scope of this study. Over the past decade, the rise of ridesourcing services, such as Uber and 99, has introduced new alternatives, making them a widely adopted shared mobility option among the population. More recently, the city has also invested in other shared mobility solutions, such as a bike sharing system. This docked system (known as Bike Rio or Bike Itaú) comprises around 5,000 shared bikes available at over 300 stations (Bike Itaú, n.d.), predominantly located in high-density areas such as the city center and coastal tourist neighborhoods (Fig. 3).

2.2. Data collection

2.2.1. Survey design and application

We designed a survey containing the following question groups: I) Revealed preference information; II) Stated choice experiment; III) Public transport (PT) interruptions; IV) Shared mobility services (ridesourcing and bike sharing) usage and assessment; V) Socioeconomic information.

In the first question group, we collected revealed preference information about the respondent's most frequent trip (e.g., origin, destination, modes, departure and arrival times, etc.). We defined the most frequent trip as the trip to the most frequently visited destination in the past week. This trip was considered because it reflects dominant mobility patterns and has a significant impact on transportation and mobility strategies. Furthermore, the most frequent trips tend to be those considered essential or necessary, such as trips to work or school/university, meaning that even in the event of disruptions in the transportation system, they would likely be adapted as they cannot be avoided (Azolin et al., 2020).

Stated choice data capture individuals' preferences for transport modes by considering variations in attributes across different scenarios (Hensher, 1994). These experiments help identify factors influencing choice, especially transportation attributes (Rose and Bliemer, 2009) and reveal preferences not accessible through observed behavior. They also allow for obtaining information about respondents' intentions to adopt new transport options under different circumstances and hypothetical scenarios (Walker et al., 2018).

A stated choice experiment was developed to identify the respondents' choice if the current PT mode they use (for their most

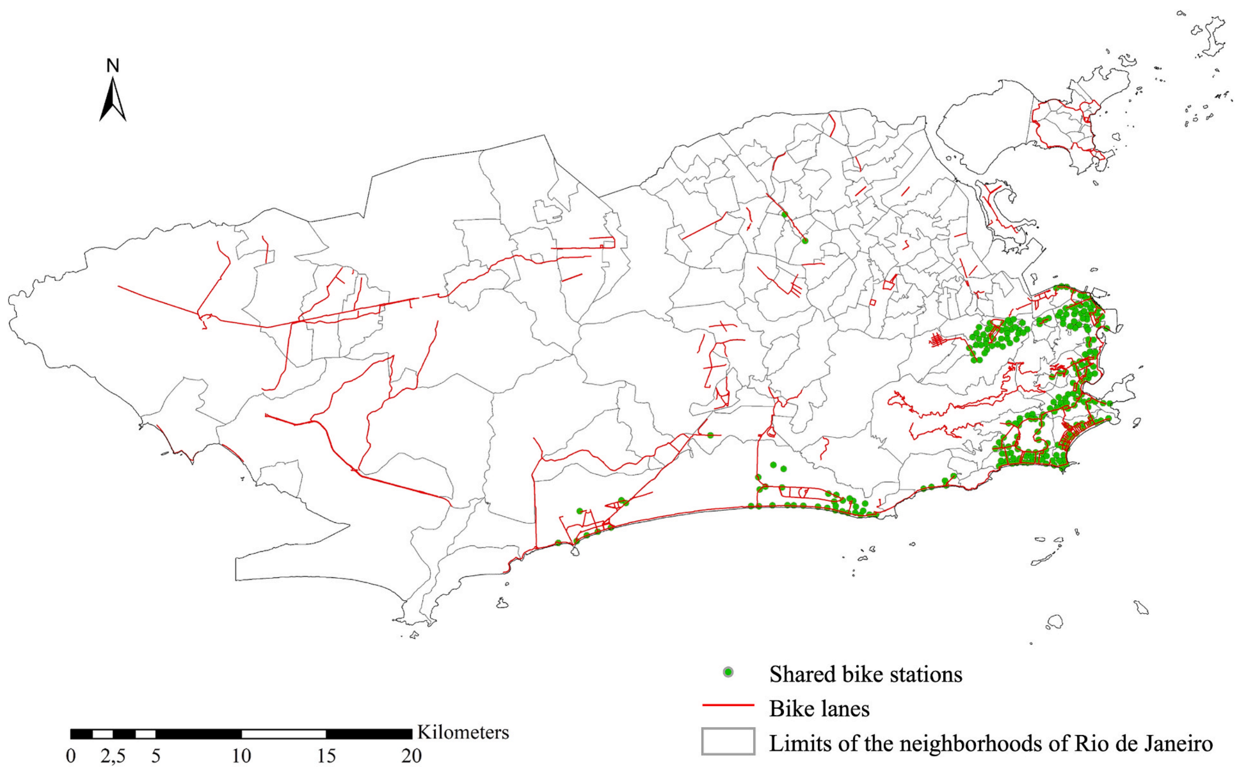

Fig. 3. Cycling infrastructure.

frequent trip) was not operational (questions group II). We conducted an experimental design with 3 alternatives, 2 attributes, and 3 levels using SAS software (SAS Institute Inc., 2023), and 18 scenarios were generated (%MktExm macro for efficient designs). We chose to use only 3 alternatives and 2 attributes to reduce the complexity of the experiment, considering the limitations of the survey administration method (paper-based) and the potential for respondent dropout with overly lengthy experiments. 3 levels were defined for each attribute to achieve greater precision and sensitivity in obtaining information about participants' preferences, capturing potential non-linear effects (Rose and Bliemer, 2009). To enhance efficiency and reduce participant fatigue, the 18 scenarios were divided into two blocks of 9, composing questionnaires Q1 and Q2.

The 3 alternatives were: bike sharing (e.g., BikeRio/Itaú), ridesourcing (e.g., Uber, 99), and PT. Ridesourcing and bike sharing are typically assigned different roles within the transportation system. Ridesourcing services can act either as a substitute for or a complement to PT, depending on contextual factors such as spatial coverage and travel time (Kong et al., 2020). In contrast, although bike sharing can occasionally replace private vehicles or PT for daily trips, its use is generally limited to short-distance travel and is more commonly adopted as a first-/last-mile solution (Chiou and Wu, 2024). Despite these different use cases, we included both modes in our choice experiment to investigate how users respond when their usual mode becomes unavailable due to a disruption, aiming to capture behavioral responses under conditions where users may consider alternatives that would not typically be part of their usual travel choices.

Given the experiment's goal, we use the strategy of defining two branches: A) for those who primarily use bus or BRT for their most frequent trip, and B) for those who primarily use metro, train, or LRT for their most frequent trip. We considered the primary transport mode as the only mode, or the mode used for the longest duration during the trip. Thus, among the 3 alternatives, the one referring to PT corresponds to metro/train/LRT or bus/BRT, depending on whether the respondents fell under branch A or B, respectively. In each scenario, respondents also had the options to "not make the trip" or to walk (only for trips classified as short distances).

We found in the literature on shared mobility several attributes that can influence mode choice, such as monetary cost, travel time, waiting time, access and egress distance/time, crowdedness, reliability, and flexibility, among others (De Sá and Pitombo, 2021; Geržinič et al., 2023; Montes et al., 2023). In our experiment, we considered travel time and monetary cost as attributes, as they are crucial factors in mode choice decisions due to their direct impact on individuals' convenience and affordability.

Travel time affects the efficiency and convenience of a transportation mode, with shorter durations being generally preferred. Long travel times in public transport can discourage its use and lead users to switch to shared modes if those options are faster (Montes et al., 2023). Monetary cost also has a significant impact, as lower expenses make a mode more attractive, especially for budget-conscious individuals. Although travel time and cost are often correlated, this relationship depends on tariff policies and system characteristics. A study in Rio de Janeiro (Herszenhut et al., 2022) showed that their interaction influences mode choice analysis, allowing individuals to balance time efficiency with economic viability when selecting a mode. In addition, in a hypothetical situation of an interruption in the transport system (emergency nature), some factors may not be as relevant as time and cost, since these can be constraints for choice (e.g., time limit to get to work, financial feasibility to opt for a particular mode).

As potential values to be assigned as attribute levels for time and cost can vary considerably depending on the trip distance, another branch of the experiment was established: 1) short distances; and 2) long distances. This strategy is commonly used in similar studies to address the challenge of setting fixed levels for the attributes (De Sá and Pitombo, 2021; Hensher et al., 2005). Even though the average speeds vary among the modes of transport considered in each group, we deemed this simplification acceptable given the variation of 3 levels, which enables comparisons between higher and lower values for each transportation group. The threshold between "short

Table 1
Attributes and levels for each alternative.

1. Short distances					
Attributes	Levels	Bike sharing	Ridesourcing	Public transport	
				(A) Metro/Train/LRT	(B) Bus/BRT
Time	1	10 min	10 min	10 min	15 min
	2	20 min	15 min	15 min	20 min
	3	30 min	20 min	20 min	25 min
Cost	1	BRL 2.00	BRL 6.00	BRL 4.60	BRL 4.05
	2	BRL 4.00	BRL 10.00	BRL 6.90	BRL 6.08
	3	BRL 6.00	BRL 14.00	BRL 9.20	BRL 8.10
2. Long distances					
Attributes	Levels	Bike sharing	Ridesourcing	Public transport	
				(A) Metro/Train/LRT	(B) Bus/BRT
Time	1	45 min	20 min	20 min	30 min
	2	1 h	30 min	30 min	45 min
	3	1 h 15 min	40 min	40 min	1 h
Cost	1	BRL 6.00	BRL 15.00	BRL 4.60	BRL 4.05
	2	BRL 8.00	BRL 25.00	BRL 6.90	BRL 6.08
	3	BRL 10.00	BRL 35.00	BRL 9.20	BRL 8.10

Note: BRT – Bus Rapid Transit. LTR – Light Rail Transit. In August 2023, BRL 10.00 (Brazilian Reais) were equivalent to approximately USD 2.05 and EUR 1.90.

distances” and “long distances” was established as 22 min for bus/BRT and 15 min for metro/train/LRT.

Table 1 shows the 3 levels considered for each attribute and each alternative in cases classified as short distances and long distances. These levels were set with a consistent variation between them, seeking to establish values within a relatively wider range to obtain distinguishable options, but not overly extensive to avoid leading to dominant alternatives (Rose and Bliemer, 2009). For the time attribute, approximate times were determined to ensure a certain equivalence between modes while presenting reasonable and easily interpretable values.

Access time (or distance) to transport was treated as a “fixed” aspect in the hypothetical scenarios to avoid introducing another attribute, which would increase the complexity of the experiment. For bike sharing, respondents were instructed to consider that a bicycle is available at a walking distance of 2 to 4 min. This is certainly not the real scenario for a large part of the population in Rio de Janeiro. However, this experiment allows evaluating the hypothetical circumstance of infrastructure improvement for this mode. Although the survey did not explicitly distinguish between docked and dockless systems, and instead focused on the availability of a nearby bike, it is reasonable to assume that respondents interpreted the option based on the system they are familiar with (docked system). In the case of ridesourcing, there is no access time because it is a door-to-door alternative. For PT, respondents were instructed to consider the nearest PT station.

For the cost attribute, the price of a single ticket for short trips on a shared bike at the time of the survey design was BRL 5.90 (Bike Itaú, n.d.), which was approximately EUR 1.12 (August 2023). Considering the possibility of plans that offer reduced per-ride costs and thinking about encouraging the use of bike sharing, we defined levels with more attractive prices to make this mode more competitive and assess its probability of being chosen. For ridesourcing, cost levels were defined based on estimating fare calculations (Portal 99app, 2022; Taxi How Much, 2022) and tests conducted on the apps during weekdays at different times of the day, also seeking to establish coherent and competitive hypothetical values.

Regarding PT, the prevailing fares during the survey design period were considered as lower levels (Rio de Janeiro, 2023), while values with + 50 % and + 100 % were considered as medium and high levels, respectively. By presenting different attribute levels in each alternative, it is possible to analyze how participants respond to variations in these attributes and what their priorities are when making choices among the presented alternatives. Therefore, not using the exact current fare values is not an issue, as the variation between levels is maintained and the value ranges are realistic. The assigned levels are approximations, as the scope of this study does not incorporate integration between transport modes. Thus, these variations are implicitly considered as the established hypothetical levels.

In the third part of the questionnaire (group III), we included questions about disruptions to the transport system that had already been experienced and their consequences in terms of mode choice. Group IV focus on ridesourcing and bike sharing services. We asked about the frequency of use of shared modes and the situations that lead to their use. Respondents also evaluated several statements on a

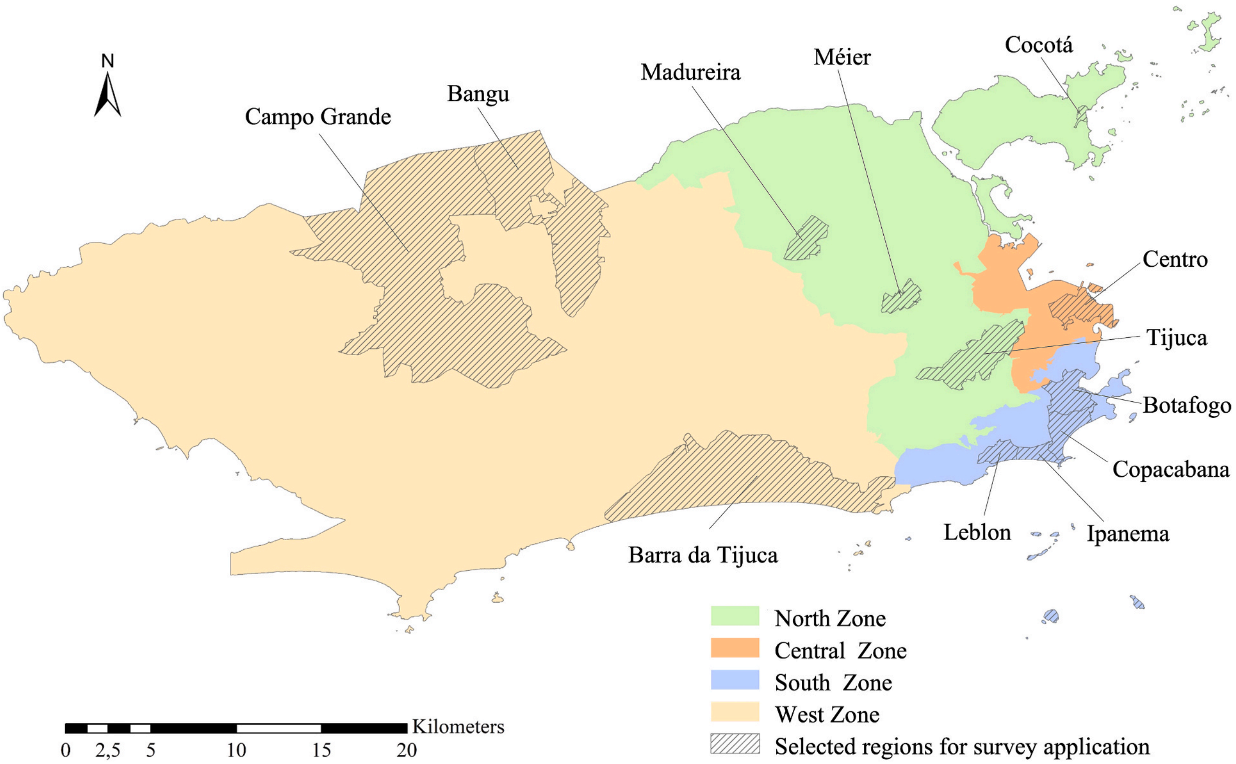

Fig. 4. Survey application regions.

5-point Likert scale regarding the provision of these services, their opinions, and their ability to use them. In the last questions (group V) we collected individual and household information (e.g., gender, year of birth, level of education, household income, vehicle ownership, etc.).

A convenience sampling strategy was employed, with recruitment conducted in person at high-flow public transportation (PT) stations across different zones of the city. To enhance diversity and representation, a stratified selection of survey locations was adopted based on the four main zones of Rio de Janeiro: Central, North, South, and West. The sampling frame consisted of PT users present at the selected stations, which were chosen based on observed daily mobility patterns to capture a diverse range of commuters. The physical presence of individuals at these strategic stations served as a practical proxy for accessing the target population of public transport users. For each city zone, the following regions were defined for application (Fig. 4): Central Zone – Centro (Central do Brasil Station); North Zone – Madureira, Méier, Tijuca, and Cocotá (ferry terminal); South Zone – Botafogo, Copacabana, Ipanema, and Leblon; and West Zone – Campo Grande, Bangu, and Barra da Tijuca (Alvorada and Jardim Oceânico stations).

Since the stated choice experiment was structured into two branches (Q1 and Q2), efforts were made to obtain a balanced number of responses for each version of the questionnaire, ensuring proportional coverage of attribute-level combinations across the experimental design. A specialized company was contracted to carry out the questionnaire administration. The interviewers received training under our supervision to ensure proper understanding of the questions and an appropriate approach when interacting with respondents. All interviews were conducted face-to-face with PT users in the city of Rio de Janeiro who voluntarily agreed to participate.

A pilot survey was conducted to assess the comprehension and coherence of the questions and to test the digital administration process using tablets and smartphones. Applicators reported significant challenges during the trial, not only concerning participant acceptance but also due to difficulties arising from technology usage (internet connectivity and app usability) and the feeling of insecurity in public spaces. We proceeded with a paper-based administration, which, although limiting questionnaires to a fixed structure and requiring additional time for tabulation, eliminated technical issues and ensured the inclusion of individuals without access to such technology. The final version of the survey instrument, translated into English for reference, is available in Appendix.

The data collection was carried out between May 22nd and June 23rd, 2023, collecting data from 1045 interviews. The survey was submitted and approved by the Research Ethics Committee of Federal University of Rio de Janeiro.

2.2.2. Built environment data

Built environment data were also collected, as factors such as public transport availability, cycling infrastructure, land use, and crime statistics may influence mobility choices. The locations of PT stations and routes, bike lanes, neighborhood boundaries, and land use were obtained from Data.Rio (2024), a portal that provides regularly updated data from the Rio de Janeiro Municipality. Data on shared bike stations were sourced from OpenStreetMap (2024). Population data were obtained from preliminary data report from the most recent Census (IBGE, 2023). Crime records for the year 2022 were provided by the Rio de Janeiro Public Security Institute (ISP, 2023).

2.3. Methods for data analysis

We conducted data preprocessing and cleaning to eliminate missing values and inconsistencies. To assess the reliability of respondents' evaluations of shared mobility modes, we applied Cronbach's Alpha test. To understand users' opinions about bike sharing and ridesourcing services, we evaluated their assessment of the service, including availability, accessibility, infrastructure, and safety perceptions.

Due to the extremely low bike sharing ridership and its minimal relevance in user decision-making in the hypothetical scenarios, this mode was not included as an alternative in the choice modeling. Instead, an exploratory analysis was conducted to understand the factors influencing its adoption. To assess spatial disparities in the availability of bike stations, we applied Gini Index and Moran's I statistic to evaluate the density and the proximity index of bike stations across neighborhoods. Given that Rio de Janeiro includes large non-urban areas (e.g., a forest and lakes), the density was calculated as the number of stations per urbanized area in each neighborhood. The proximity index was defined as the number of stations within a 1 km radius of the population-weighted centroid of each neighborhood, considering network distances.

To explore the factors influencing the use of bike sharing services, we conducted preliminary association tests and a logistic regression analysis. We assessed the relationship between bike sharing usage and categorical and numerical variables, applying Chi-square and Mann-Whitney tests (non-normal data distribution), respectively. In the logistic regression model the dependent variable was the binary indicator (1 = user, 0 = non-user), and the independent variables included age, race, income, education, private vehicle and bike ownership, digital access, proximity to bike sharing stations, and crime index. Crime index was determined as the number of public road-related crimes recorded per 1,000 inhabitants on the neighborhood of origin (ISP, 2023).

A mixed logit model was applied to analyze user choices between three alternatives: ridesourcing, PT, and none (opt-out alternative, grouping low-choice options). Grouping alternatives with minimal selections helps maintain statistical robustness when an alternative lacks sufficient data for reliable estimation. Mixed logit model was chosen to account for heterogeneity in preferences across individuals, with panel data structures to handle repeated observations per respondent. Time and cost coefficients were modeled as random parameters following a triangular distribution to ensure a reasonable spread while maintaining interpretability (Hensher et al., 2005; Train, 2009).

Explanatory variables included individual factors (age, gender, race, education, income, digital access, private car/motorcycle ownership, PT fare benefits, ridesourcing usage), trip-related factors (short/long distance, purpose, peak/off-peak hour), and environmental factors measured at the origin location (population density, PT proximity index, crime index). To prevent multi-collinearity issues, we assessed highly correlated and strong associated variables using: Pearson's correlation coefficient between numerical variables ($r > 0.7$); Chi-square test and Cramer's V between categorical variables ($V > 0.3$); and Kruskal-Wallis test for numerical vs. categorical variables ($\eta^2 > 0.14$), given non-normality verified by the Shapiro-Wilk test (Cohen, 1998).

Variables (both direct effects and interaction terms) were added iteratively, assessing their statistical significance and contribution to model fit. The utility function for each alternative j (U_j) were specified in Eq. (1). Multiple models were tested and refined to identify the most appropriate one. The final model retained only statistically significant variables and interactions.

$$U_j = \beta_{0,j} + \beta_{T,j}T_j + \beta_{C,j}C_j + \sum \beta_{X,j}X + \sum \beta_{X,T_j}XT_j + \sum \beta_{X,C_j}XC_j + \epsilon_j \tag{1}$$

where $\beta_{0,j}$ is alternative-specific constant. For the attributes related to the alternatives, time (T_j) and cost (C_j), an alternative-specific formulation (distinct parameters) was used, assuming that variations in these attributes are perceived differently for each alternative (Ben-Akiva and Lerman, 1985) and to capture differences in user sensitivity to these attributes across modes. $\beta_{X,j}$ is the coefficient for variables related to the individual, the trip, and the environment (X) inserted with direct effect in the utility. As these variables do not vary across alternatives, they should be included in the model in a specific form (Train, 2009). Interaction terms (XT_j and XC_j) captured heterogeneity in user preferences and variations in the impact of these attributes on transportation choices.

An important measure of willingness to pay (WTP) in transportation research is the value of travel time savings (VTTS), which represents the monetary amount an individual is willing to spend to reduce their travel time by a specific unit (Hensher et al., 2005). To determine the VTTS, we followed the widely accepted approach of computing the ratio between the time and cost coefficients, as recommended in the discrete choice modeling literature (Hensher et al., 2005; Train, 2009). The general VTTS was first estimated using unconditional parameters derived from the model. Additionally, individual-specific estimates were obtained using a conditional distribution approach, which provides a more behaviorally consistent measure of WTP by conditioning the estimated parameters on the chosen alternatives, thereby reducing the likelihood of extreme values in the distribution (Train, 2009). Furthermore, subgroup-specific WTP values were obtained by segmenting the sample based on variables that significantly interacted with the attributes.

The analyses were conducted using R scripts (R Core Team, 2023), and the Apollo package (Hess and Palma, 2019) was used for mixed logit model estimation. Maps were generated using QGIS (QGIS Development Team, 2023).

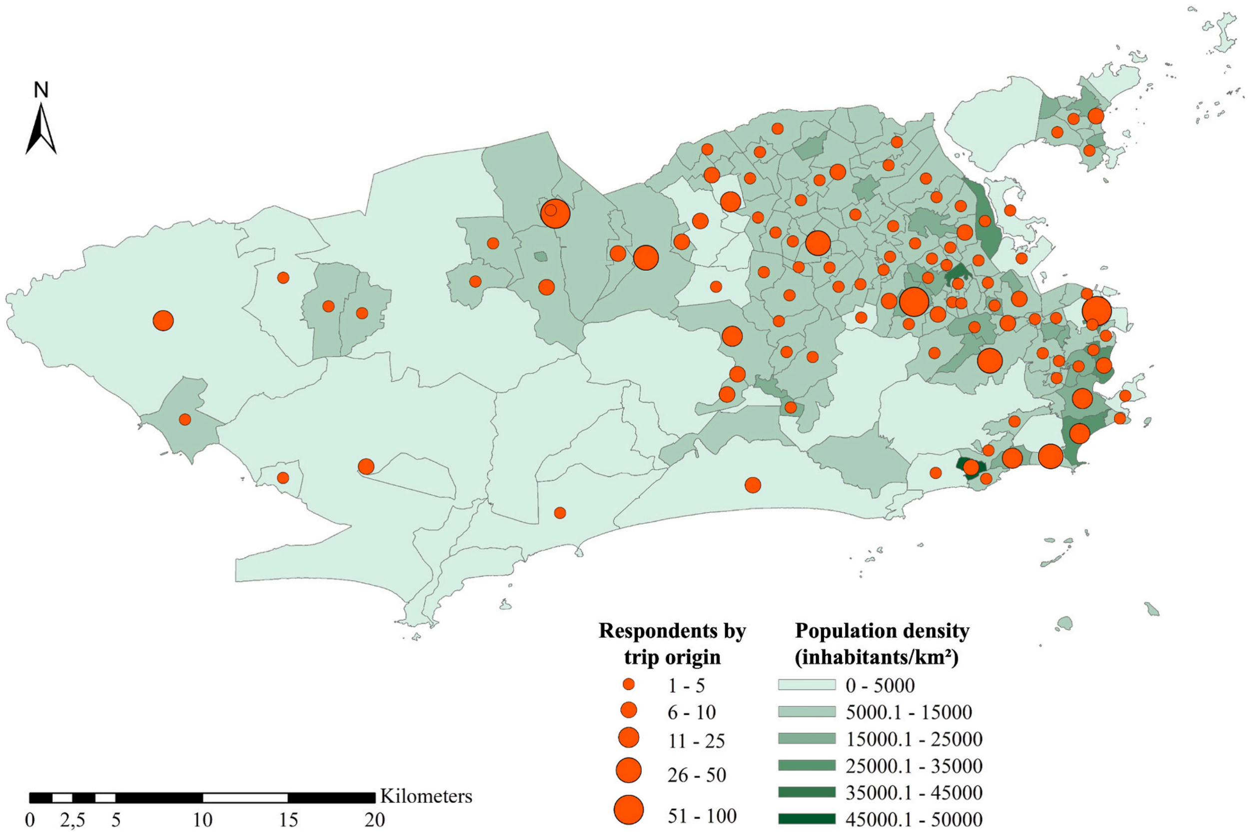

Fig. 5. Respondents by origin and population density of neighborhoods.

3. Results and discussions

3.1. Sample and descriptive statistics

After conducting data pre-processing and cleaning to eliminate missing data and inconsistencies, we excluded data from trips outside the city limits. As a result, out of the 1,045 interviews, 852 valid responses remained. We found adequate internal consistency of shared modes assessments (Cronbach's alpha = 0.812). Fig. 5 illustrates the distribution of respondents according to their origin and the population density of neighborhoods, showing that respondents are concentrated in the most densely populated areas of the city,

Table 2
Sample composition.

Variable	Sample (N = 852)	Ridesourcing user (N = 782)	Bike sharing user (N = 81)	Census 2022
Gender				
Male	43.3 %	42.2 %	40.7 %	46.4 %
Female	56.2 %	57.3 %	58.0 %	53.6 %
Other/No answer	0.5 %	0.5 %	1.2 %	–
Age				
16–34 years old	52.9 %	54.7 %	65.4 %	27.8 %
35–64 years old	43.2 %	42.5 %	34.6 %	41.2 %
65 years old and older	3.9 %	2.8 %	0.0 %	14.4 %
Education				
Low	12.3 %	11.0 %	7.4 %	35.3 %
Medium	68.8 %	70.8 %	61.7 %	39.9 %
High	16.7 %	16.1 %	28.4 %	24.8 %
No answer	2.2 %	2.0 %	2.5 %	
Monthly household income				
Up to 1 NMW	17.8 %	17.4 %	13.6 %	39.54 %[c]
1 to 3 NMW	47.3 %	48.0 %	48.1 %	35.22 %[c]
More than 3 NMW	32.0 %	31.8 %	35.8 %	25.24 %[c]
No answer	2.8 %	2.8 %	2.5 %	
Race				
White	36.6 %	36.8 %	49.4 %	45.4 %
Black	20.7 %	19.9 %	18.5 %	15.6 %
Mixed race	40.4 %	41.2 %	30.9 %	38.7 %
Other/No answer	2.3 %	2.0 %	1.2 %	0.3 %[a]
Private car / motorcycle / bike ownership				
0	75.7 % / 94.0 % / 79.6 %	76.7 % / 94.5 % / 79.2 %	53.1 % / 87.7 % / 66.7 %	
1	23.6 % / 5.6 % / 16.4 %	22.9 % / 5.1 % / 17.3 %	45.7 % / 11.1 % / 28.4 %	
2	0.7 % / 0.4 % / 3.4 %	0.4 % / 0.4 %. / 3.1 %	1.2 % / 1.2 % / 3.7 %	
3 or more	0.0 % / 0.0 % / 0.6 %	0.0 % / 0.0 % / 0.5 %	0.0 % / 0.0 % / 1.2 %	
Payment benefit for PT				
None	93.5 %	94.4 %	93.8 %	
Student Pass	1.1 %	1.0 %	1.2 %	
Special Pass	1.1 %	0.9 %	0.0 %	
Free University Pass	0.9 %	1.0 %	3.7 %	
Senior Pass	3.2 %	2.4 %	0.0 %	
No answer	0.2 %	0.3 %	1.2 %	
Digital access				
No	3.9 %	1.5 %	0.0 %	
Yes	96.1 %	98.5 %	100.0 %	
Main mode group[b]				
Bus/BRT	42.3 %	43.2 %	48.1 %	
Metro/LRT/Train	57.7 %	56.8 %	51.9 %	
Trip distance				
Short	20.0 %	19.9 %	27.2 %	
Long	80.0 %	80.1 %	72.8 %	
Trip time				
Off-peak	50.8 %	51.9 %	49.4 %	
Peak	49.2 %	48.1 %	50.6 %	
Trip purpose				
Job	70.1 %	70.2 %	69.1 %	
Study	7.2 %	7.2 %	12.3 %	
Other	22.8 %	22.6 %	18.5 %	

Note: Education: Low – Elementary or lower, Medium – High school, High – University degree or higher. 1 NMW (National Minimum Wage) corresponds to R$ 1,320 (Brazilian reais), equivalent to USD 270.44 and EUR 250.33 (August 2023 values). PT – Public transport. BRT – Bus Rapid Transit. LTR – Light Rail Transit. [a] Asian and Indigenous. [b] No respondent had the ferry boat as their main mode. [c] The preliminary data from the 2022 Census (IBGE, 2023) released up to the time of this study's development do not yet include information on income, therefore, income data from the 2010 Census are presented (IBGE, 2012).

which suggests a reasonable alignment between the sample distribution and the urban population pattern. Pursuant to the goal of applying a comparable quantity of both Q1 and Q2 questionnaires, 49 % of the interviews were conducted using Q1, while 51 % employed Q2.

Table 2 summarizes the respondents' distribution, considering the total sample (852), those who use ridesourcing with some frequency (782, i.e. 91.8 %), and those who use bike sharing with some frequency (81, i.e. 9.5 %). Based on preliminary data available from the 2022 Census (IBGE, 2023), our sample is relatively well-distributed in terms of gender and race.

The sample consists primarily of young women with a medium level of education and moderate household income. The data shows that most respondents lack access to private transportation, with most not owning cars, motorcycles, or even bikes. This high dependence on public transport highlights the distinction between mobility in the Global South and the Global North. Digital access is very high, with nearly all respondents owning smartphones with internet access, indicating that technological infrastructure is not a major barrier for this specific group.

Tables 3 and 4 present the use of ridesourcing and bike sharing among respondents and their experience with disruptions in PT service, respectively. The findings highlight distinct user behaviors regarding shared mobility services. Ridesourcing is widely used, with 91.8 % of users reporting usage at least in specific situations, whereas bike sharing has limited adoption, as 90.5 % of respondents never use it. Circumstances that lead to ridesourcing use include PT unavailability (32.0 %), the absence of a private car (22.3 %), and after drinking alcoholic beverages (19.4 %). Meanwhile, bike sharing is mainly motivated by exercise (55.6 %) and other reasons, such as leisure (23.5 %). Regarding previous experiences with disruptions in PT, 76.4 % of respondents have encountered them. Among these respondents, the main alternative was another PT mode (73.6 %), followed by ridesourcing (11.4 %), private car (1.8 %), and shared bikes (0.3 %). This highlights existing barriers to using shared modes, particularly shared bikes. Vehicle breakdowns (55.9 %) were the primary reported cause of disruptions, followed by public safety issues (22.7 %).

Table 5 presents the distribution of choices in the stated choice experiment. Across all presented scenarios, most respondents preferred an alternative public transport option (63.7 %). However, when focusing on individuals making short trips, ridesourcing was chosen in most scenarios (42.9 %). Active modes, including bike sharing, were considered in very few cases, with opting out of the trip being more frequent than choosing these modes.

3.2. *Bike sharing*

The assessment of the bike sharing system (Fig. 6) reveals that a significant proportion of respondents were unfamiliar with bike sharing services and did not feel capable of evaluating key aspects, especially regarding price (87.5 %), bike availability (70.8 %), and safety (accidents: 71.4 %; thefts/robberies: 69.8 %). Among those who provided evaluations, aspects related to availability and convenience, such as service accessibility, adequate infrastructure, and conveniently located stations, showed noticeable disagreement levels, suggesting potential room for improvement in service accessibility. Aspects related with capability (physical ability and familiarity with app) and benefits of using this service (lower price and avoid traffic jams) received predominantly favorable responses. Concerns regarding safety are evident, with a considerable share of respondents disagreeing that they feel safe from thefts/robberies or accidents. The large proportion of respondents who did not feel capable of assessing several aspects also suggests limited knowledge about the service, which may impact the general perception and overall adoption.

From the collected data, we identified the low use of the bike sharing service by public transport users, both in their previous experiences (Table 3) and in the hypothetical scenarios of disruption to their usual public transport (Table 5). The spatial disparity in the availability of bike sharing services and their concentration in a specific area of the city, already visible in Fig. 3, was confirmed by analyzing both the density of stations per neighborhood (Gini index = 0.8785; Moran's I statistic = 0.6404, p-value < 0.00) and the

Table 3
Use of ridesourcing and bike sharing among respondents.

Frequency of use	**Ridesourcing** (N = 852)	**Bike sharing** (N = 852)
Never	8.2 %	90.5 %
Rarely	26.4 %	4.9 %
Occasionally	49.9 %	3.3 %
Frequently	15.5 %	1.3 %
Circumstances of use*	**Ridesourcing user** (N = 782)	**Bike sharing user** (N = 81)
After drinking alcoholic beverages	19.4 %	1.2 %
Maintain social distance	0.8 %	0.0 %
No private car	22.3 %	3.7 %
PT unavailable	32.0 %	4.9 %
PT insecurity	17.9 %	0.0 %
Crowded PT	0.0 %	1.2 %
Weather conditions	7.9 %	–
Congested traffic	–	9.9 %
Practice exercise	–	55.6 %
Ridesourcing unavailable	–	0.0 %
Other (e.g., leisure)	13.8 %	23.5 %

Note: * – Respondents were able to choose more than one circumstance of use. PT – Public transport.

Table 4
Experience with disruptions in public transport service.

Frequency	Sample (N = 852)	Ridesourcing user (N = 782)	Bike sharing user (N = 81)
Never	23.6 %	22.6 %	24.7 %
Rarely	45.1 %	45.8 %	51.9 %
Occasionally	22.4 %	22.6 %	17.3 %
Frequently	8.9 %	9.0 %	6.2 %
Reason for disruption	**Sample*** (N = 651)	**Ridesourcing user*** (N = 605)	**Bike sharing user*** (N = 61)
Vehicle breakdown/failure	55.9 %	57.2 %	49.2 %
Public safety issues	22.7 %	22.3 %	23.0 %
Power outage	7.4 %	7.3 %	14.8 %
Strikes	4.9 %	4.6 %	6.6 %
Heavy rain	4.1 %	4.0 %	1.6 %
Other	4.9 %	4.6 %	4.9 %
Alternative option	**Sample*** (N = 651)	**Ridesourcing user*** (N = 605)	**Bike sharing user*** (N = 61)
Other PT available	73.6 %	74.2 %	59.0 %
Ridesourcing	11.4 %	12.2 %	24.6 %
Bike sharing	0.3 %	0.2 %	0.0 %
Private car	1.8 %	1.0 %	3.3 %
Walk	0.6 %	0.7 %	1.6 %
Other	10.9 %	10.7 %	11.5 %
No trip	1.4 %	1.0 %	0.0 %

Note: * – Part of the sample that has already experienced some interruption in the public transport system. PT – Public transport.

Table 5
Distribution of choices in the stated choice experiment.

	Sample* (N = 7668)	Short trips (N = 1530, 20 %)	Long trips (N = 6138, 80 %)
Bike sharing	0.5 % (40)	1.0 % (16)	0.4 % (24)
Ridesourcing	27.3 % (2095)	42.9 % (656)	23.4 % (1439)
Alternative PT	63.7 % (4884)	40.9 % (626)	69.4 % (4258)
Walk	1.3 % (97)	6.3 % (97)	–
No trip	7.2 % (552)	8.8 % (135)	6.8 % (417)

Note: * – Each respondent made the choice for 9 scenarios (total choice sample: 852 x 9 = 7668). PT – Public transport.

proximity index (Gini index = 0.9084; Moran's I statistic = 0.4169, p-value < 0.00). This suggests a significant spatial concentration in areas near the city center and tourist neighborhoods, highlighting the need for more equitable distribution of adequate and safe cycling infrastructure and bike sharing stations.

Preliminary association tests were conducted to explore the factors influencing the use of bike sharing services. Age, race, education, and private vehicle ownership showed significant associations with bike sharing usage. Younger individuals and white users were more likely to use the service (Chi-square test: $\chi^2 = 7.65$, $p = 0.020$; $\chi^2 = 5.69$, $p = 0.017$, respectively), and higher education levels ($\chi^2 = 9.81$, $p = 0.007$) were positively associated with increased usage. Ownership of private cars or motorcycles ($\chi^2 = 25.07$, $p < 0.001$) and private bikes ($\chi^2 = 8.32$, $p = 0.004$) also positively influenced adoption. Proximity to bike stations was a relevant factor (Mann-Whitney test, $W = 20730$, $p < 0.001$), with users living significantly closer to stations (median = 7) compared to non-users (median = 0). Gender, income, digital access, and PT benefits did not show significant associations.

The logistic regression confirmed the significance of key predictors (Table 6). Being young, owning a private car or motorcycle, and owning a private bike significantly increased the chances of using bike sharing services. Proximity to bike sharing stations also had a positive impact. Being white was marginally significant at the 90 % confidence level. Although income was not statistically significant, this result may be related to the predominance of a narrow income range within the sample. Private vehicle ownership is often considered a proxy for higher-income populations, suggesting that this factor may indirectly capture the influence of income. The results also show that cycling habits contribute to the use of bike sharing services, which, based on the discussed findings, still appear to be primarily associated with leisure activities and exercise.

3.3. Ridesourcing

In the case of ridesourcing services, respondents demonstrated greater familiarity, with only 8.2 % having never used them (Table 3). Additionally, 32.0 % reported the unavailability of PT as a motivator for using this service (Table 3), highlighting its potential use during PT disruptions.

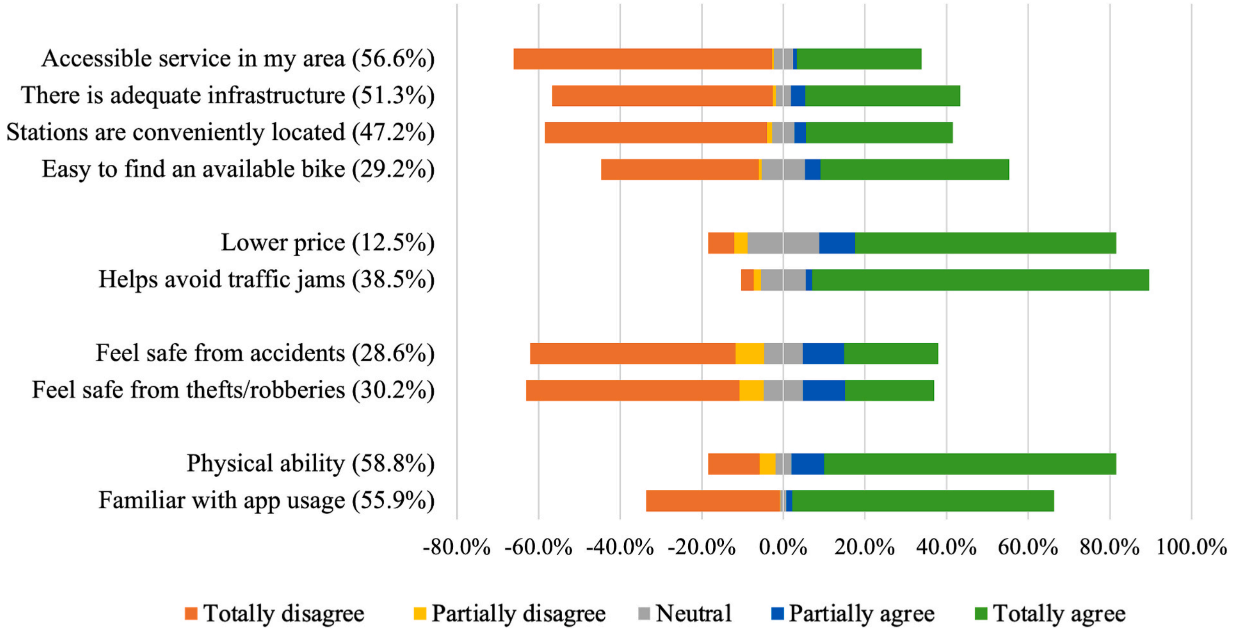

Fig. 6. Assessment of the bike sharing service**.** Note: Values in parentheses indicate the proportion of respondents who considered themselves capable of assessing each aspect.

Table 6
Logistic regression results for factors associated with bike sharing usage.

	Coefficient		Odds ratio	CI 95 %
Intercept	−3.973	***	0.0188	[0.006 – 0.046]
Young (binary)	0.752	***	2.1221	[1.266 – 3.643]
White (binary)	0.452	*	1.5721	[0.957 – 2.582]
Education				
Low (ref.)	–		–	–
Medium	0.087		1.0906	[0.467 – 3.003]
High	−0.077		0.9262	[0.339 – 2.82]
Private car/motorcycle (binary)	1.086	***	2.9632	[1.719 – 5.105]
Private bike (binary)	0.784	***	2.1912	[1.280 – 3.694]
Proximity index (bike sharing stations)	0.086	***	1.0893	[1.050 – 1.130]
Crime index	−0.004		0.9961	[0.990 – 1.002]
Log-likelihood	−229.00			
Pseudo R^2 (McFadden)	0.12			
Pseudo R^2 (Nagelkerke)	0.16			
AIC (Akaike)	475.99			

Note: The crime index includes crimes occurring on public roads. ***, * – significance levels of 1% and 10%, respectively.

Fig. 7 shows respondents' evaluations of various aspects of ridesourcing services. The percentages in parentheses indicate the proportion of respondents who felt capable of assessing each aspect. The high response rates across all aspects (values in parentheses) demonstrate that ridesourcing is a widely used and familiar mode of transportation in Rio de Janeiro. Overall, most respondents expressed positive perceptions of ridesourcing services, with most agreeing or strongly agreeing with the statements presented. The highest levels of agreement were observed for aspects such as service accessibility in their area (94.8 %) and familiarity with app usage (90.5 %). The benefit of avoiding traffic jams and safety-related aspects, concerning thefts or robberies and accidents, received the most negative evaluations, with disagreement proportions of 18.6 %, 12.8 %, and 12.1 %, respectively.

The results of the mixed logit model estimated from the stated choice experiment data are presented in Table 7. Travel time and cost showed significant negative coefficients, indicating that increases in these variables reduce the probability of choosing the respective mode, as expected. The sensitivity to time is stronger for ridesourcing (μ = -0.120) than for PT (μ = -0.086), suggesting that users are more averse to time delays when considering ridesourcing services. This may reflect the perception of ridesourcing as a faster, more convenient mode compared to PT, making time an even more critical factor. The cost sensitivity is significant for both modes, with public transport users being more sensitive to fare increases (ridesourcing μ = -0.516; PT μ = -0.858). The variability in cost sensitivity is greater for PT, as indicated by the larger standard deviation (σ = 1.088 compared to σ = 0.329 for ridesourcing), suggesting that cost preferences for PT users are more heterogeneous. The alternative-specific constant for choosing none of the options (−6.306)

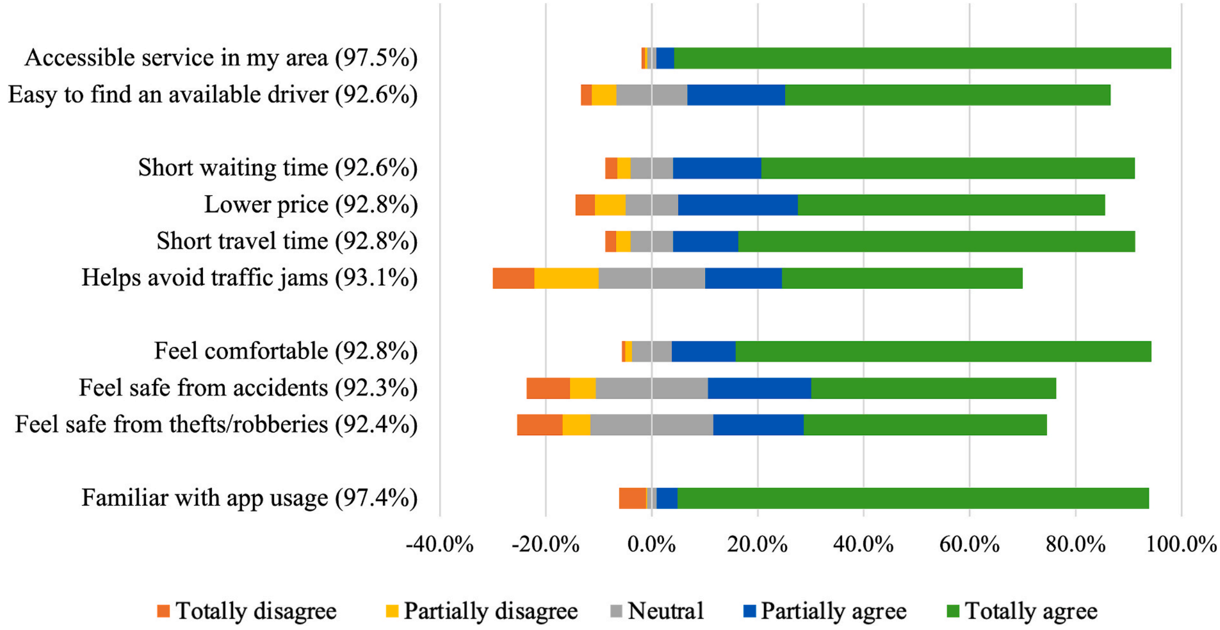

Fig. 7. Assessment of the ridesourcing service. Note: Values in parentheses indicate the proportion of respondents who considered themselves capable of assessing each aspect.

Table 7
Estimates of the mixed logit model.

	Coefficient		Rob. S.E.	Rob. t-value
Constants				
asc_PT	ref.		–	–
asc_Ridesourcing	−1.219		0.870	−1.401
asc_None	−6.306	*	0.824	−7.656
Attributes				
Time – Ridesourcing (μ)	−0.120	*	0.013	−9.284
Time – Ridesourcing (σ)	−0.248	*	0.022	−11.325
Time – PT (μ)	−0.086	*	0.012	−6.941
Time – PT (σ)	−0.208	*	0.020	−10.579
Cost – Ridesourcing (μ)	−0.516	*	0.058	−8.967
Cost – Ridesourcing (σ)	0.329	*	0.042	7.920
Cost – PT (μ)	−0.858	*	0.167	−5.132
Cost – PT (σ)	1.088	*	0.103	10.609
Other variables (direct effect)				
Long trip – Ridesourcing	2.561	*	0.976	2.623
Long trip – PT	2.498	*	0.939	2.660
High income – Ridesourcing	3.471	*	0.820	4.230
High income – PT	2.852	*	0.944	3.019
PT proximity index – Ridesourcing	0.073	*	0.015	4.760
PT proximity index – PT	0.062	*	0.016	3.781
Peak hour – Ridesourcing	3.739	*	0.698	5.358
Other variables (interaction)				
Long Trip * Cost Ridesourcing	0.285	*	0.055	5.208
Long Trip * Cost PT	0.798	*	0.174	4.573
Age > 65 * Time Ridesourcing	−0.160	*	0.054	−2.969
Peak hour * Cost Ridesourcing	−0.115	*	0.031	−3.688
Final log-likelihood	−2965.23			
AIC	5972.46			
BIC	6117.24			
Adjusted Rho-squared	0.5187			
Number of draws for random parameters (MLHS)	2000			

Note: * – Significant coefficients at the 99% confidence level. PT – Public transport.

highlights that opting out of transport was the least chosen option in the choice experiment.

Both ridesourcing and PT see increased utility for longer trips, but the slightly higher magnitude of the coefficient for ridesourcing suggests that it may be perceived as more suitable for longer-distance travel, potentially due to its flexibility and comfort. The higher magnitude of the utility coefficient for ridesourcing also suggests that higher-income individuals may find this mode particularly attractive. Proximity to available PT stations positively affects both PT and ridesourcing. This could be related to the fact that areas with good public transport access also tend to support ridesourcing services, while also reflecting the potential role of ridesourcing as a complementary mode connecting with PT networks.

The interaction effects provide additional insights into how trip characteristics and demographics influence mode preferences. The interaction between long trips and cost shows that users are less sensitive to cost when traveling longer distances. This effect is stronger for PT, suggesting that users view PT as a more cost-effective option for long trips compared to ridesourcing. In contrast, older users (Age > 65) show a negative interaction with time for ridesourcing (interaction coefficient = -0.160), indicating that longer trip durations discourage them from choosing ridesourcing.

During peak hours, cost negatively influences ridesourcing usage (interaction coefficient = -0.115), suggesting that high fares during peak periods deter price-sensitive users from choosing this mode. However, the positive effect of peak travel on ridesourcing utility (coefficient = 3.739) indicates that ridesourcing services remain more attractive during peak times, potentially due to greater flexibility and reliability compared to public transport during congestion. This contrast suggests heterogeneity among users: those with lower cost sensitivity may continue to favor ridesourcing during peak periods despite the higher fares, while cost-sensitive users may shift to alternatives such as public transport.

The general value of travel time savings (VTTS) for ridesourcing was 13.98 BRL/hour (0.23 BRL/minute), which was approximately 2.66 EUR/hour (0.044 EUR/minute). For PT, the VTTS was 6.01 BRL/hour (0.10 BRL/minute), equivalent to 1.14 EUR/hour (0.019 EUR/minute). These values indicate that, on average, users exhibit a higher willingness to pay for travel time savings in ridesourcing compared to PT, particularly in situations of disruption. Fig. 8 presents VTTS estimates segmented by trip distance, peak and off-peak hours, and user age, as these variables significantly interacted with time or cost attributes in the model. The VTTS for ridesourcing is consistently higher than for PT across all groups. The differences between the two modes are particularly pronounced for longer trips and during peak hours, where ridesourcing exhibits a substantially higher VTTS compared to PT. Older individuals (Age > 65) have a VTTS that is more comparable between the two modes. As expected, given the lack of significance in the interaction term, the VTTS for PT remains the same between peak and off-peak hours.

4. Conclusions

This study aimed to evaluate the potential use of shared mobility services (ridesourcing and bike sharing) during disruptions in public transport operation, focusing on the user's perspective. A survey was conducted among PT users in the city of Rio de Janeiro, including a stated choice experiment to assess their probability of adopting these services when their usual PT mode is unavailable.

The findings indicate that bike sharing remains a rarely used mode, with limited knowledge regarding its usage, infrastructure, and potential benefits. Its adoption appears to be primarily restricted to leisure and exercise and is not regarded as a viable alternative during public transport disruptions. Spatial analysis and logistic regression revealed that proximity to bike sharing stations, being younger, white and owning a private vehicle (typically associated with higher affordability) increase the chances of shared bikes use, consistent with related literature. However, respondents did not choose this option even when nearby stations were proposed in the stated choice experiment during public transport disruptions (only 0.5 % opted for bike sharing). This suggests that equitable station distribution alone is not enough to increase adoption. Beyond expanding access, measures such as safe cycling infrastructure and affordable trial incentives (e.g., free first rides) could help encourage greater use. Due to the minimal relevance of bike sharing in users' decision-making, we focused the discrete choice model on the other alternatives.

In contrast, ridesourcing proved to be a widely recognized and frequently used mode, with a significant portion of respondents reporting its usage in various circumstances, including PT unavailability. The stated choice experiment results confirm the strong potential of ridesourcing to support the transportation system during disruptions. It was chosen as an alternative across different trip characteristics and user segments, with a higher willingness to pay for travel time savings compared to PT. Furthermore, the mixed logit model results indicate that cost sensitivity varies among users, with some groups being more likely to choose ridesourcing despite higher fares. Proximity to public transport infrastructure was found to influence ridesourcing adoption, suggesting that it may function as a complementary mode during PT disruptions.

Unlike most previous research on PT disruptions, which has primarily examined operational effects and network responses, this study focuses on individual preferences and behavioral responses to shared mobility alternatives. Our findings highlight the importance of designing user-centered strategies to improve the accessibility and attractiveness of shared mobility services, particularly bike sharing. While ridesourcing appears to have strong potential in mitigating the impacts of PT disruptions, the findings suggest that planners must address significant challenges if they aim to promote bike sharing as a more sustainable and non-motorized alternative. The low awareness and lack of familiarity with bike sharing indicate that making it a viable transport option requires specific strategies, including a more equitable spatial distribution of adequate cycling infrastructure and bike sharing stations, information and marketing, and initiatives such as free trials to increase trust and confidence in the service.

Despite its contributions, this study has some limitations that should be addressed in future research. The sample was limited to PT users, not capturing broader perceptions of shared mobility modes among the general population. The stated choice experiment was constrained by the limitations of paper-based data collection, resulting in a restricted number of attributes. Including attributes such as access/egress time, crowding levels, and comfort could improve the analysis. For the same reason, we had to group PT modes and did

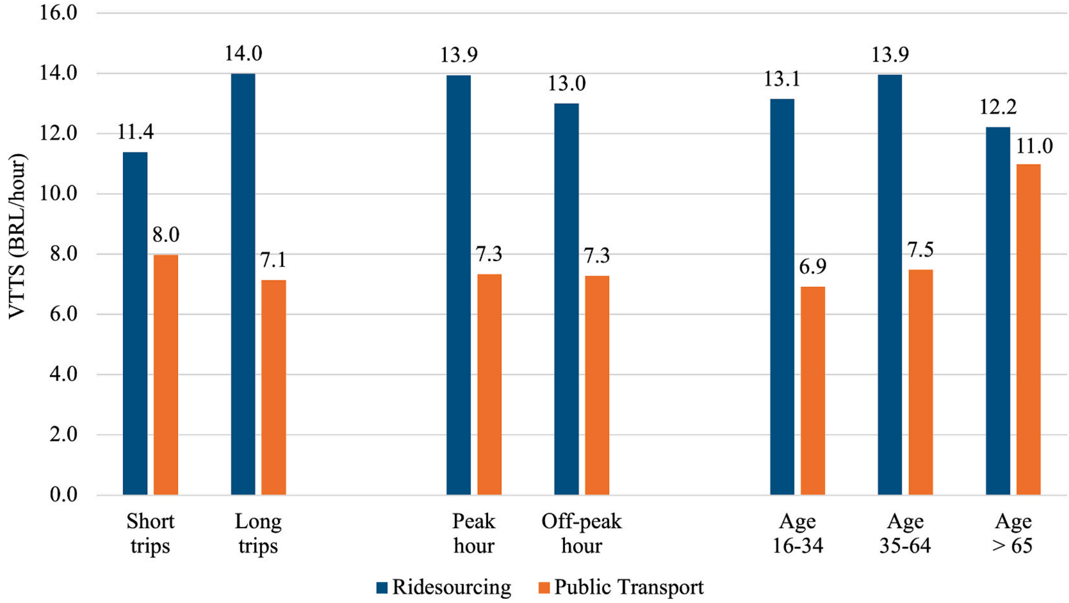

Fig. 8. Values of travel time savings (VTTS) by groups. Note: VTTS – Value of travel time savings. In August 2023, BRL 10.00 (Brazilian Reais) were equivalent to approximately USD 2.05 and EUR 1.90.

not consider the integration between modes as an option. The effects of different types of disruptions were beyond the scope of this study, although they may influence how users perceive and evaluate alternative modes.

Although in the stated choice experiment respondents were instructed to consider a hypothetical scenario in which bike sharing would be available near their origin aiming to assess its potential use, the influence of limited access under current conditions and lack of familiarity was still reflected in the overall results. The extremely low selection rate for bike sharing in the experiment made it unfeasible to include this mode in the discrete choice modeling. Future studies in cities with similar disparities in service availability could explore bike sharing more specifically, incorporating a preliminary awareness stage to ensure that respondents are sufficiently informed to meaningfully evaluate and consider the service in the experimental scenarios. The integration of revealed and stated preference data for trips involving shared modes is also an important direction for future research.

CRediT authorship contribution statement

Luiza Gagno Azolin: Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Anna Beatriz Grigolon:** Writing – review & editing, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Antônio Nélson Rodrigues da Silva:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Karst T. Geurs:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

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 A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2025.104972.

Data availability

The data that has been used is confidential.

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